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王者以民为天，而民以食为天

----司马迁，《史记·酈生陆贾列传》

Rulers who honor the kingly way regard the people as heaven, and the people regard food as heaven.

--- BC. 94, Sima Qian, Records of the Grand Historian

Note: Heaven means most important and vital.

Heaven (天 Tian) is a sacred and fundamental concept in ancient Chinese philosophy. It has three different meanings. The first is the physical sky or the entirety of nature (not including human society), the operations of which manifest certain laws and order. The second refers to a spiritual being, which possesses an anthropomorphic will and governs everything in the universe. The third denotes the universal law, which is observed by all things and beings, and which is also the basis of human nature, morality, and social and political orders.

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No one can catch time but they can expand life! I still remember my first impression when I got off the flight from Beijing to Frankfurt. Everything was appealing, and I was filled with curiosity accompanied by excitement and nervousness. I could not help going out and looking around even before dawn. Now it is evening, also maybe the end of my time in Germany, and it seems I spent one day from beginning to end.

During these five years, I tried to find out more about myself and Germany as well. Jogging and hiking are the two most favourite part-times. I began to enjoy the calm very much. Moreover, I am a little afraid of crowded people that a Chinglish translation is “People mountain people sea”. Besides, I became familiar with cold food, including fresh, raw vegetable. I believe I’ve become half German.

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Fang Yin

Halle, February 2020

Abstract

Demand for agricultural products has been increasing at an unprecedented pace, particularly in rapidly growing economies such as China. Agricultural imports to China have soared despite domestic production increasing manifold since reforming and opening in 1978. However, the increase in agricultural production in China involved high environmental costs, brought about by massively increasing input intensity and by the transition in cropping patterns. In this thesis, I analysed environmental and socioeconomic data at county level to develop a solid quantitative understanding of patterns, determinants, and causes of agricultural land-use changes across all of China from 1980 to 2011. In Chapter II and Chapter III, I summarized the changes in patterns of the main crops at county level. I then examined these data with exploratory spatial data analysis and spatially explicit panel regressions in order to identify the spatial and temporal determinants of changes in area and yield of major crops. In chapter IV, I used the same dataset, but focussed on changes in technical efficiency in crop production using a stochastic frontier approach, again by employing spatial econometric panel analysis. Overall, the spatial concentration of the major crops increased, with population the main determinant for this trend. Furthermore, modern inputs, including machinery and fertilizer, were increasingly important in crop production, and land use efficiency increased slightly and varied temporally and spatially. This analysis shed light on the patterns and drivers of agricultural land-system change for all of China, including insights on hotspots of changes in land use extent and intensity. Besides, the elasticity of input changes showed the growth of crop production was shift from traditional farming practices to modern. This study is valuable to inform and spatially target land-use policies in China and provide important case evidence for global land-use change.

Zusammenfassung

Die Nachfrage nach Agrarprodukten hat rapide zugenommen, besonders in schnell wachsenden Volkswirtschaften. Agrarimporte nach China gestiegen, trotz der vielfach gestiegenen Inlandsproduktion seit der Reform und Öffnung 1978. Jedoch ging die Steigerung der Agrarproduktion einher mit hohen Umweltkosten, zum einen durch eine massive Erhöhung der Inputintensität und zum anderen durch die Veränderung der Anbaumuster. In dieser Arbeit habe ich umwelt- und sozioökonomische Daten auf Kreis-Ebene analysiert, um ein grundlegendes quantitatives Verständnis der Muster, Determinanten und Ursachen der landwirtschaftlichen Landnutzungsveränderung in China von 1980 bis 2011 zu entwickeln. In Kapitel II und III habe ich die Veränderung der Anbaumuster der Hauptkultur auf Kreisebene zusammengefasst. Ich habe diese Daten mittels explorativer Geodatenanalyse und räumlich expliziter Panel-Regression untersucht, um raum-zeitliche Determinanten der Änderung in Anbaufläche und Ertrag der Hauptkultur zu identifizieren. In Kapitel IV nutzte ich diese Daten, um die Veränderung der Technischen Effizienz in der Pflanzenproduktion mit Hilfe eines stochastischen Grenzansatzes zu ermitteln, wiederum durch den Einsatz einer räumlich-ökonometrischen Panel-Analyse. Insgesamt hat sich die räumliche Konzentration von Hauptkulturen erhöht. Haupteinflussfaktor für diese Entwicklung war die Bevölkerung. Diese Analyse beleuchtet die Muster und Treiber des agrarwirtschaftlichen Landnutzungswandel für gesamt China und gibt Einblicke in die Brennpunkte des Wandels in Landnutzungsumfang und –intensität. Außerdem zeigten die Elastizitäten der Input-Veränderungen einen Trend in der Pflanzenproduktionsintensität von traditionell zu wissenschaftlich-technologischen Eingriffen. Die Ergebnisse können zur Einwicklung räumlich ausgerichteter Landnutzungspolitiken in China beitragen. Sie stellen außerdem wichtige Fallbeweise für den globalen Landnutzungswandel zur Verfügung.

Contents

Acknowledgement	i
Abstract	iii
Zusammenfassung	v
Contents	vi
List of figures	viii
List of tables	x
List of appendix	xii
List of abbreviations	xiv
<hr/>	
Chapter I. Introduction	1
1. Background	2
1.1 Food security	2
1.2 Agricultural land use change	5
2. Methodology	7
2.1 Spatial econometrics	7
2.2 Efficiency and productivity	9
3. Study area	11
4. Data	14
5. Objectives, research questions and methodology	16
Appendix I	19
<hr/>	
Chapter II. Cropland and major crops increasing concentration	25
Abstract	26
1. Introduction	27
2. Materials and Methods	30
2.1 Data	30
2.2 Spatial Clustering	31
2.3 Inequality of Distribution of Cropland and Harvested Area of Crops	33
3. Results	34
3.1 Spatial Clustering	34
3.2 Inequality of Distribution of Cropland and Harvested Area of Crops	37
4. Discussion	39
5. Conclusions	41
Appendix II	43
<hr/>	
Chapter III. Determinants of changes of cropland and major crops	49
Abstract	50
1. Introduction	51
2. Data	54
3. Methodology	57
4. Results	59

4.1	Changes in harvested area and yield	59
4.2	Determinants of the changes	60
5.	Discussion	63
6.	Conclusion	65
	Appendix III	67
Chapter IV. Changes in land use efficiency		75
1.	Introduction	77
2.	Methodology	79
2.1	The spatial autoregressive frontier model	79
2.2	Technical efficiency and determinants model	81
2.3	Land use efficiency	81
3.	Data	82
3.1	Output and input variables	83
3.2	Technical inefficiency determinants	84
3.3	Spatial weight matrix	85
4.	Results	86
4.1	Parametric estimates of the spatial autoregressive frontier function	86
4.2	Estimates of technical inefficiency model	89
4.3	Land use efficiency analysis	91
5.	Discussions	93
6.	Conclusions	94
	Appendix IV	96
Chapter V. Synthesis		99
1.	Summary	100
2.	Significance	104
3.	Critical reflections and Outlook	105
3.1	Critical reflections	105
3.2	Outlook	106
References		109
Eidesstattliche Erklärung		131

List of figures

Figure I-1. The harvested area changes of cereal and five major crops in the world and China.	15
Figure I-2. Land use distribution in China in 2010.....	16
Figure II-1. Distribution of cropland and the five major crops in 2011.....	31
Figure II-2. Two perspectives on concentration and methods for quantification.	32
Figure II-3. Global Moran's I of cropland and five crops from 1980 to 2011.	35
Figure II-4. LISA cluster maps for cropland area from 1980 to 2010 in 10-year intervals.	36
Figure II-5. LISA cluster maps for harvested area of maize for 1980, 1990, 2000, and 2010.	37
Figure II-6. Generalized entropy index for cropland and for the harvested areas of the five selected crops (a) and decomposed harvested area of the five crops with the sum indicating total inequality (b).	38
Figure III-1. Main cultivation region of each crop (thick black outline) with the harvested area values in 2011.....	56
Figure III-2. Trends of explanatory variables within the main cultivation regions of rice, wheat, maize, and soybean.....	57
Figure III-3. Changes in harvested areas and yields in the main cultivation regions.	59
Figure III-4. Percentage change in harvested areas of each crop with a 1% increase in the explanatory variables; markers are coefficient estimates, and whiskers denote the 95% standard errors.....	61
Figure III-5. Percentage change in yields of each crop with a 1% increase in the explanatory variables; markers are coefficient estimates, and whiskers denote the 95% standard errors.....	61
Figure III-6. Variable importance for changes in harvested areas of each crop; dots are standardized coefficients, and whiskers denote the 95% standard errors.	62
Figure III-7. Variable importance for changes in yields of each crop; dots are standardized coefficients, and whiskers denote the 95% standard errors.	63
Figure IV-1. Annual elasticities from 1981 to 2011 with respect to inputs in whole China and regions.	88
Figure IV-2. Technical efficiency change from 1981 to 2011.....	89
Figure IV-3. Densities of technical efficiency.	90
Figure IV-4. Spatial distribution of technical efficiency in 2011 and trends in each province.....	91
Figure IV-5. Annual changes in land use efficiency.....	91
Figure IV-6. Relationship between the sown area and technical efficiency (TE) and land use efficiency (LUE) (a), and the quantile-quantile plot between TE and LUE (b).	92
Figure IV-7. Distribution of land use efficiency.....	93

List of tables

Table IV-1. Variables and summary statistics.	84
Table IV-2. Estimation of spatial autoregressive production function and technical inefficiency.	87

List of appendix

A I-1. The relationships between different spatial dependence models for cross-sectional data.	19
A I-2. Key datasets required for analysis in this study.	20
A I-3. Agricultural land and cropland in the world and China (sources from FAOSTAT 2019).	21
A I-4. Productions of cereal and five major crops in world and China.	22
A I-5. Yields of cereal and five major crops in world and China.	23
A I-6. Comparison the cropland data from remote sensing and statistics.	24
A II-1. Counties, provinces, and regions of China.....	43
A II-2. LISA maps of harvested areas of crops.....	44
A II-3. Generalized entropy index and the harvested area changes from 1980 to 2011.....	47
A II-4. Moran's I of cropland with different neighbourhood matrices.	48
A III-1. Yield distribution of four crops in 2011.	67
A III-2. Area changes in four major crops in 10-year intervals.	68
A III-3. Yield changes in four major crops in 10-year intervals.....	70
A III-4. Estimations from log-log regression with its 95% standard error.	73
A III-5. Estimations from standard regression with its 95% standard error.	74
A IV-1. Study area.	96
A IV-2. Models test and specification.	97

List of abbreviations

FAO	Food and Agriculture Organization
SDG	Sustainable Development Goals
Mha	million hectare
LUCC	Land-use/ cover change
IGBP	International Geosphere-Biosphere Program
IHDP	International Human Dimensions Program on Global Environmental Change
GLP	Global Land Project
LCS	Land change science
LSS	land system science
SAR	Spatial Autoregressive Model
SLM	Spatial Lag Model
SEM	Spatial Error model
SAC	Spatial Autocorrelative Model (with spatial lag and spatial error term)
SDM	Spatial Durbin Model
SLX	Spatial lag of X
AIC	Akaike information criterion
BIC	Bayesian information criterion
GEI	General entropy index
TE	Technical efficiency
DEA	Data envelop analysis
SFA	Stochastic frontier analysis
LUE	Land-use efficiency
GDP	Gross domestic product
DEM	Digital elevation model
GDD	Growing degree days
RTA	regional trade agreement
TPP	Trans-Pacific Partnership
RCEP	Regional Comprehensive Economic Partnership
TTIP	Transatlantic Trade and Investment Partnership

Chapter I. Introduction

1. Background

1.1 Food security

Food is a fundamental human need. Food security is high on the global policy agenda and is currently an enormous challenge. According the Food and Agriculture Organization (FAO) World Food Summit in 1996, “food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life” (FAO, 1996). It includes availability, access, utilization and stability (Stephens et al., 2018). Zero hunger is the second target in Sustainable Development Goals by 2030 (United Nations, 2015). Demand for food is increasing as populations grow and gain wealth to consume more varied and resource-intensive diets. There is an increased competition for land, water, energy, and other inputs to food production (Tilman et al., 2011). The broad-ranging goals are to end hunger, achieve food security, improve nutrition and promote sustainable agriculture. There is more than enough food to feed everyone on our planet, yet in 2018, still 820 million (11% of global population) people suffered from hunger, with numbers increasing since 2010 mostly in developing countries of Africa, Latin America and the Caribbean, and even Asia (FAO et al., 2019). Meanwhile, food waste in developed countries is 222 million tons annually (McCarthy et al., 2018). As a result, food security is a complex and challenging issue to resolve, not only related to production but also location.

Globally, as a synthetic system, food security is connected to the environment (Delzeit et al., 2017) and economic development (Grafton et al., 2015). Since the industrial revolution, urbanization has both expanded and intensified across the globe, resulting in accelerated land use change. In sub-Saharan Africa, food demand is expected to increase by 300% by 2050 due to the accelerating growth of the human population (van Ittersum et al., 2016). To meet the increasing demand for food and feed, the input intensity of land use has been substantially increased. For example, in some areas the use of agricultural machinery and fertilizer and pesticide inputs per unit area have increased more rapidly than crop yields, indicating lower input use efficiency (Lassaletta et al., 2014). Insufficient use of agricultural inputs, particularly nitrogen, has led not only to poor yields in terms of quantity and of nutritional value, but also to depletion of soil fertility (ten Berge et al., 2019). Such changes put pressure on the limited arable land resources. As the global population grows and its consumption patterns change, additional land will be required for living space and agricultural production. Biodiversity is threatened by agriculture greater than

by any other human activity, since agriculture uses and contaminates land and water (Garnett et al., 2013). The scarcity of land restricts production increases, leaving high intensification as the only possibly efficient land use. Meanwhile, environmental damage is a double-edged sword, both leading to and caused by cropland expansion. Hence, it remains crucial to highlight opportunities and challenges for more efficient use of resources in agricultural production.

Starting around 9,000 BC, the agriculture has developed independently in several regions of the globe. Intentionally and unintentionally, human have reshaped the terrestrial biosphere (Dearing et al., 2006; Turner et al., 1990), through hunting and gathering and the increasingly permanent use of land for agriculture and settlements (Ellis et al., 2010; Ellis and Ramankutty, 2008). Agriculture provides the livelihood for 40% of the world's population, the single largest employment sector in the world. It is also the largest source of income and jobs for poor, rural households, employing about 60% of workers in less-developed countries (United Nations, 2020). Hand-in-hand with agriculture, environmentally transformative human use of land area has accelerated (Stephens et al., 2019). Furthermore, an important element in the history of agriculture is the human-induced spatial movement of plants and animals the world over (Beddow and Pardey, 2015). Globalization of agricultural production, such as the rapidly-growing quantity, quality, and distance of internationally-traded agriculture and food products, has resulted in land use changing between telecoupled locations and spill-over effects between two systems, supply-side and consumption-side, which suggests that trade constitutes a central driver for loss in ecosystem carbon in the regions with cropland expansion (Karstensen et al., 2013; Kastner et al., 2014; Levers and Müller, 2019). The interaction and trade between regions and countries require the researchers to consider agriculture not only in small regions or a specific case, but also globally.

Agricultural land use expanded markedly after 1700 but with substantial geospatial heterogeneity (Klein Goldewijk et al., 2011). Since at least the late Pleistocene (around 12,000 BC), the long-term impacts from forest clearing have been evident: increased fire frequencies, mega faunal extinctions, species invasions, soil erosion and others (Ellis et al., 2013; Kirch, 2005). In many tropical areas, forests continue to be converted to agriculture, leading to biodiversity loss, increasing greenhouse gas emissions, and depleting of critical ecosystem services (Bommarco et al., 2018; Eitelberg et al., 2016; Foley et al., 2011). This is a remarkable impact on the biosphere caused by only one species, human, and one half of all human biomass appropriation occurs on cropland (Haberl et al., 2007). Further

expansion into the tropics, however, will add relatively little to global food supplies because most production gains have been achieved through intensification on existing agricultural land (Garnett, 2014). In temperate regions, agricultural land area started to decrease in 1991, particularly in marginal areas, while intensification continued increase in suitable agricultural areas (Nin-Pratt, 2015; Tilman et al., 2011; Van Asselen and Verburg, 2013). Globally, for the period between 1960 and 2013, agricultural food production increased by a factor of 3.25 with a 8.6-fold increase in nitrogen fertilization, a 3.9-fold increase in phosphorus fertilization, but only a 1.1-fold increase in agricultural land (FAO, 2019). However, expansion, contraction, intensification, and de-intensification of agriculture varied greatly from place to place, with considerable variation both at the global level but also within individual countries and regions.

Grains are still by far the world's most important sources of food, both for direct human consumption, such as rice and wheat, and indirectly, as inputs to livestock production, including maize and soybean. Rice, wheat, maize and soybean currently produce nearly two thirds of global agricultural calories (FAO, 2019; Ray et al., 2013).

Rice (*Oryza sativa* (Asian rice) or *Oryza glaberrima* (African rice)), traditionally, has been the staple food and main source of income for millions of people, and it will continue to be a mainstay of life for future generations. Rice is the predominant staple food for 17 countries in Asia and the Pacific, nine countries in North and South America and eight countries in Africa. It is the staple food of over half the world's population. About 87% of rice is produced in Asia and about 95% of the world's rice is produced in developing countries where rice is also an important item in international trade. Rice provides 20% of the world's dietary energy supply (FAO, 2019).

Wheat (*Triticum aestivum*) is the dominant crop in temperate countries, used for both human food and livestock feed (Shewry, 2009). It is counted among the "big three" cereal crops, with over 200 million hectare (Mha) and 770 million tons harvested in 2017 (FAO, 2019). Wheat supplies 19% of the world's dietary energy. Accounting for a fifth of the world's food, wheat is the main source of protein in developing countries and is second only to rice as a source of calories in those consumers' diets. By 2050, demand for wheat in the world is projected to increase by 60% (Hertel et al., 2010).

Maize (*Zea mays*), also called corn, is believed to have originated in central Mexico 7000 years ago from a wild grass, and Native Americans transformed maize into a better source of food. It provides 5% of total dietary energy supply in the world (FAO, 2019). Maize is

grown throughout the world, with the United States, China, and Brazil being the top three maize-producing countries, producing approximately 563 of the 717 total million tons/year globally. Maize can be processed into a variety of food and industrial products, including starch, sweeteners, oil, beverages, glue, industrial alcohol, and fuel ethanol (Ranum et al., 2014).

Soybeans (*Glycine max*) supply the world a needed source of protein and oil required for growth. The increase in soybean production has been impressive, since 1960 global production has increased 420% in harvested area and 1212% in production. Three countries, Brazil, Argentina and the U.S., produced over 82% of the world's soybeans. Meanwhile, China is the largest country of soybean consumption, accounting for 32% in 2018 (FAO, 2019). Crop conversion from soybean to wheat, maize, rice and vegetables in importing countries because of the competitive advantage in producing countries caused N pollution (excess over growth requirement that ended up as runoff, leaching, and losses to the atmosphere) (Sun et al., 2018).

Potatoes (*Solanum tuberosum*) are the third most important food crop in the world with 19.3 Mha and 388 million tons harvested in 2017 (FAO, 2019). Originating in the Andes Mountains of South America, today it is widely cultivated (Hawkes, 1992). Potatoes can grow up to 4,700 meters above sea level and from southern Chile to Greenland. China is the world's largest potato producer, with the proportion of harvested area increasing by 343% since 1961, accounting for around 30% of harvested area and over a quarter of worldwide fresh potato production in 2017 (FAO, 2019).

1.2 Agricultural land use change

The demand to increase agricultural production is unprecedented with current population growth and consumption of increasingly varied and resource-intensive diets. It is a pivotal force that is changing the environment, and balancing growing food production with environmental protection is a key challenge for humanity. However, there is no measurement or analysis for the complicated linkage of agriculture and the environmental system. Land is the nexus of competing development claims and of crucial societal and environmental challenges and opportunities to address food security. In recent years, agricultural land has expanded globally, but many temperate regions have experienced a decline in cultivated area, with a net redistribution of agricultural land toward the tropics. Agricultural land is the principal link between human activities and environment, but faces myriad vulnerabilities, such as water-soil erosion, and fertilizer and pesticide pollution.

Such areas become unsuitable for planting, let alone viable for increasing production sustainably. Economic development amplifies and accelerates agricultural land conversion, including the effects of displacement, rebound, cascade and remittance.

Land use change is a key process of global environmental change, which refers to two major processes: the first process is change in land cover associated with the expansion or contraction of the area of land used for different purposes (e.g. pasture, cropland, urban); the second process is a change in the type of management on existing land cover (Meyfroidt et al., 2018; van Vliet et al., 2016). Land-use/ cover change (LUCC) has already entered the global sustainability science agenda with the International Geosphere-Biosphere Program (IGBP) and the International Human Dimensions Program on Global Environmental Change (IHDP) developed in 1994 and continued with the Global Land Project (GLP) (Lambin and Geist, 2006). The increasing demand of humans for ecosystem services, food production and nature protection, require changes in the extent and intensity of land use (Meyfroidt et al., 2018; Stephens et al., 2019). Understanding land-use change is crucial for designing strategies to address sustainability challenges, such as climate change, food security, energy transition, and biodiversity loss (Eitelberg et al., 2016; Meyfroidt et al., 2018).

Land change science (LCS), or land system science (LSS), is a fundamental component of global environmental change and sustainability research. In LCS, monitoring, understanding and modelling are the key components. Understanding the past and current situation will help us incorporate adaptive changes to reach the goal of sustainability. Quantitative methods for understanding changes in land use are well-developed in land systems science (Geist and Lambin, 2004; Meyfroidt, 2016). The drivers of land use change have been discussed extensively (Magliocca et al., 2014; van Vliet et al., 2016). Drivers include increases in human population, with additional food requirements, changes in the types of food as wealth and urbanization rates increase, demand for energy and fibre, and enhanced transportation and development of roads (Alexander et al., 2015; Nath et al., 2015; Seekell et al., 2017). Land use policies and globalization were other important factors for land use change (Babcock, 2015; Nepstad et al., 2014; Sun et al., 2018; Sun et al., 2019). Consequently, it becomes an essentially multidisciplinary research. Case studies rooted in a particular place and context have been important because they integrate data describing people, place, and environment with land use data as well as data on land use decision makers (Rindfuss et al., 2007). It is based on constructing dynamic models which aim to replicate and enhance system understanding by formalizing and exploring the

relations between different variables and their outcomes (Verburg et al., 2016). Case studies substantially differ in spatial scale and time period varying from pixel resolution to governmental boundaries, from one year with cross-sectional data to millions of years with panel data (van Vliet et al., 2016).

2. Methodology

2.1 Spatial econometrics

Tobler presented the first law of geography (Tobler, 1979): "Everything is related to everything else, but near things are more related than distant things". Spatial dependence or spatial autocorrelation is best known and acknowledged most often in the core disciplines of regional science and geography (Anselin, 1988; Getis, 2008). Besides spatial dependence, spatial heterogeneity is the second type of spatial effect, which is related to the lack of stability over space of the behavioural or other relationships under study (Anselin, 1988). Spatial economics provides a perspective consisting of spatial dependence and spatial heterogeneity that provide the solutions to carry out the proper specification, estimation, hypothesis testing and prediction for models in regional science (Gibbons et al., 2015). However, it is still a relatively young discipline in the wider scientific thought.

When location is simply a source of additional information on each unit of observation, it adds little to the complexity of analysing and understanding the causes of spatial phenomena. However, in situations where agents are able to interact, relative locations may play a role in determining the nature of those interactions. In these situations of spatial interdependence, analysis is significantly more complicated and the subject of ongoing epistemological and methodological debate. However, in situations where agents are able to interact, relative locations may play a role in determining the nature of those interactions. In these situations of spatial interdependence, analysis is significantly more complicated and the subject of ongoing epistemological and methodological debate (Anselin et al., 2008; Corrado and Fingleton, 2012; Gibbons et al., 2015).

In 2008, Paul Krugman won the Nobel Prize in Economic Sciences by clarifying the microeconomic underpinnings of both spatial economic agglomerations and regional imbalances at the national and international levels (Fujita and Thisse, 2009; Krugman, 2007, 1991). Spatial econometrics typically deals with models related to regional and urban economics. Standard econometric models restrict spatial spill-overs to be zero, while spatial econometric models assess the magnitude and significance of spatial spill-over

empirically (Elhorst and Vega, 2013). The relationships between different spatial dependence models for cross-sectional data are presented in Appendix (A I-1). The spatial autoregressive (SAR) model has received increasing attention since the 1970s (Cliff and Ord, 1975). Until 2007, spatial econometricians were mainly interested in the spatial lag model (SLM) and spatial error model (SEM) (Elhorst, 2010). In the years since, multiple spatial interaction effects have been considered. Spatial autocorrelative model (SAC) models include both a spatially-lagged dependent variable and a spatially-autocorrelated error term, and the spatial Durbin model (SDM) includes both a spatially-lagged dependent variable and spatially-lagged explanatory variables.

Recently, spatial econometrics included the time dimension with the introduction of spatial panel models that accounted for both spatial and temporal dependence in the disturbance terms (Anselin et al., 2008; Baltagi, 2005). The spatial econometrics literature has exhibited a growing interest in the specification and estimation of econometric relationships based on spatial panels (Elhorst, 2005). Panel data are generally more informative, and they contain more variation and less collinearity among the variables (Elhorst, 2003). Incorporating a locational component with panel data has two spatial effects: spatial dependence and spatial heterogeneity. These effects are adopted explicitly and are related to the independent variables (LeSage, 2008).

To catch the spatial effects, a spatial weight matrix W was introduced to describe the spatial arrangement of the spatial units (Getis, 2009). W is an $N \times N$ weights matrix, and the element W_{ij} can be set according to the research questions. It is assumed that W is a matrix of known time-invariant constants, that all diagonal elements of the weights matrix are zero to exclude the self-effect. Contiguity neighbour weight matrix and inverse distance weight matrix are the most used weight matrices. For easy interpretation, it is common practice to normalize W so that the elements of each row sum to unity. In essence, the weighting effect can be interpreted as an averaging of neighbouring values (Anselin, 2007; Elhorst, 2003).

According to the normal panel model, fixed effects and random effects are identified. In the fixed effects model, a dummy variable is introduced for each spatial unit as a measure of the variable intercept. In the random effects model, the variable intercept is treated as a random variable that is independent and identically distributed (*i.i.d.*) with zero mean and variance σ_{μ}^2 . Furthermore, it is assumed that the random variables μ_i and error terms ε_{it} are independent of each other. Therefore, spatial panel data models can include fixed effects

spatial lag models, fixed effects spatial error models, random effects spatial lag models and random effects spatial error models. In addition, more spatial interactions also can be introduced. In practice, testing for models specification is needed. The random effects model and the fixed effects model can be tested by Hausman's specification test (Baltagi, 2005), which treats the spatial dependence variable as an explanatory variable, so R^2 is also an index for model specification. Furthermore, the Wald-test is used to check whether spatial-weighted independent variables are needed. Besides, Akaike information criterion (AIC) and Bayesian information criterion (BIC) are widely used in statistical software (Belotti et al., 2013), and they made the model specification much easier with comparing the value of information loss (Burnham and Anderson, 2004).

2.2 Efficiency and productivity

When we want to know the performance of producers in economy, we naturally think of revenues and costs. It is common to describe them as more or less "efficient" or more or less "productive". Overall productivity is broadly determined by four components: production technology, scale of operation, operating efficiency, and the environment in which production occurs (Fried et al., 2008). Technology and scale effects on productivity are associated with a particular shape of the production function that specifies a relation of how much output y can be produced with any quantity of input x , such as the Cobb-Douglas Production Function. The environmental component is random variable exogenous. Technical efficiency is a measure of efficiency related to a best practice frontier e.g. the best production possibility (Farrell, 1957). This latter component could be interpreted as agents' managerial skills corresponding to a performance index.

Two front-runners emerged among the proposed approaches: Data Envelopment Analysis (DEA) that estimates maximal output and attributes all departures from this as inefficiency, and Stochastic Frontier Analysis (SFA) that allows for both unobserved variation in output do to shocks and measurement error, including inefficiency (Parmeter and Kumbhakar, 2014). DEA is the mathematical programming approach to the construction of frontiers and measurement of efficiency relative to the constructed frontiers, which truly envelops a data set regardless of noise (Simar and Wilson, 2011). SFA was first proposed independently by both Aigner et al.(1977) and Meeusen and van Den Broeck (1977) who identified one part of the error terms to capture inefficiency. Sensibly, it incorporates both noise and inefficiency into the model specification, the prime benefit being the ability to disentangle

the two error components (Fried et al., 2008). For this property, this approach can be relaxed in the presence of panel data, even combining with spatial location.

Studies on spatial stochastic frontier models have developed rapidly in recent decades. The main models accounting for spatial dependence in frontier analysis can be divided into two major groups: those that explain inefficiency/efficiency in terms of exogenous determinants analysing heterogeneity and those that account for spatial dependence by including a spatial autoregressive specification in the model (LeSage and Pace, 2009). The first study estimated a spatial error production frontier panel model in rice farming (Druska and Horrace, 2004), calculating the time-invariant technical inefficiency, and concluded that spatial correlation affects technical efficiency (TE). Glass et al. (2016) proposed a spatial autoregressive stochastic frontier model (SAR-SFA) for panel data and introduced the concept of efficiency spill-over. Besides, their term for technical inefficiency is homoscedastic, which they applied to aggregate production in Europe. Pede et al. (2018) investigated the role of the spatial dependency of dependent variable in the technical efficiency estimation of rice farmers using panel data in the Philippines, and established that the preferred option was the SAR-SFA by comparing to non-spatial spill-over. Meanwhile, Ramajo and Hewings (2018) developed a SAR-SFA model with the feature of a time-varying decay efficiency specification, which was used to estimate regional development performance in Western Europe. Most recently, a stochastic frontier model with a spatial lag structure introducing a model of technical inefficiency estimates parameters is becoming increasingly attractive and used (Glass and Kenjegalieva, 2019; Kutlu, 2018; Kutlu and Nair-Reichert, 2019; Tsukamoto, 2018).

In our research, land is understood as a terrestrial ecosystem that includes not only scarce soil resources, but also vegetation, water, landscape setting, climate attributes and ecological processes (MEA, 2005), and it is assessed by biomass efficiency (Le et al., 2014). Traditionally, the measurement of natural resources is the output per unit of input (Bergmann et al., 2017). In this thesis, land use efficiency (LUE) measures the amount of land each producer is wasting related to the best practice frontier, which is introduced from the measurement of single input efficiency and environmental efficiency (Reinhard et al., 2002, 1999). It can be measured by reducing the amount of land while keeping the amount of other inputs and the production constant (Liu et al., 2019; Zhang et al., 2018). We also delineate the spatial spill-over effects on efficiency from the overall efficiency estimation, and highlight the impact of spill-overs on land use efficiency.

3. Study area

Chinese food security has a strategic significance not only for sustained domestic economic and social development, but also for world food security. According to the global land-use products of the History Database of the Global Environment (HYDE) and Center for Sustainability and the Global Environment (SAGE) datasets, cropland in China increased steeply from 1700 to 1950, followed by a decrease after 1950 (Foley et al., 2005; Klein Goldewijk et al., 2011). Currently, 11% of land area is used for crops in China. Among such area, the major crops, including maize, rice, wheat and soybean, account for 90%. The cultivated regions of wheat decreased in northeastern China, where the crop converted mostly from wheat to rice or maize. As a result, achieving higher yields is needed for self-sufficiency. To be sure, yields increased steadily since 1964, since increasing mechanization and education on best practices have spread throughout the farming sector. However, rampant overuse of fertilizers and pesticides brings with it many problems concerning air and water pollution. China's government make a measurement to confirm its national food security status, and plans to remove 3.3 Mha of cropland for maize production from 2016 in order to 2020 to reduce environmental pollution (Cui and Shoemaker, 2018).

China is currently in its best period in history in terms of food security thanks to high grain output, abundant stocks, and stable market supply and access. China's latest five-year plan, which runs from 2016 to 2020, set two remarkable objectives for the agricultural sector: achieve self-sufficiency in cereal grains and absolute food security. China may already be largely self-sufficient in food supply, which is the ability to grow enough to feed its people. The rise in overall grain production has outstripped population growth, with per capita grain output jumping from less than 0.21 tons in 1949, the year New China was founded, to 0.47 tons in 2018. The population nearly doubled during the same period. In recent years, the nation's self-sufficiency ratio for the three major grains—rice, wheat and maize—has registered a robust 95%.

However, for pigs and other livestock, self-sufficiency is considerably different. Economic development, increasing average income of residents, globalization and urbanization, and westernized diet patterns are likely to bring increased demand for major crops, including maize, rice, soybeans, and wheat. To come up with additional supplies from domestic

production, China needs to both expand the area that is farmed and squeeze more yields out of each hectare. Besides domestic production, China must import 100 million tons of soybeans, mainly as feedstock for farm animals, making China the world's biggest importer of oilseeds.

Chinese agriculture has intensified greatly since the early 1980s, on a limited land area with large inputs of chemical fertilizers and other resources (Guo et al., 2010). China has the daunting challenge of providing enough food for more than 1.3 billion people. Moreover, the scarcity of arable land is a defining feature of Chinese agriculture. In 2015, China fed 18.9 percent of the world's population with only 8.5 percent of the world's arable land (FAO, 2019). Furthermore, the limited agricultural land resource in China is distributed to 231 million households, resulting in an average farm size of only 0.96 acres per household, and even such small farms are usually scattered in several separate plots. Therefore, China faces two challenges: (a) preserving the quantity and quality of its arable land amid rapid urbanization; and (b) consolidating land to increase agricultural productivity.

China's population has been growing rapidly since 1949 at an average growth rate of 1.5% from 542 million to 1.37 billion in 2015 according to official statistics. Meanwhile, the rural population declined by 1% on average since 1990 and even by 2% since 2010 (FAO, 2019). In addition to the massive movement from rural to urban areas, reductions in reproduction rates brought about by population control policies, endogenous choices, and increasing longevity thanks to higher medical standards has led to an aging of the society, particularly in rural areas (Deng and Li, 2016; Long et al., 2012). In sum, the rapid demographic transition in China has immense effects on the availability of rural labour, and thus on the labour input in agriculture.

Furthermore, China has experienced high economic growth rates since the reforming and opening in 1978. Annual GDP growth rates were about 10% on average between 1980 and 2015 (World Bank). Increasing incomes and affluence paved the way for a higher consumption of livestock proteins, such as beef and sheep meat per capita, which increased almost five-folds between 1980 and 2013, while pork doubled (FAO, 2019). The increasing demand for livestock products was partly satisfied through increasing imports of meat and feed but also drove substantial changes in domestic agricultural production (Zhihui Li et al., 2015). Domestic meat production increased five-fold from 1980 to 2013, and feed crops such as maize replaced major food staples, including rice and wheat (Foley et al.,

2011). For example, since 1980, the area of maize harvested increased from 20 Mha to 36 Mha (80%), while that of rice and wheat decreased by about 5 Mha (FAO, 2019). The changes in land-based production towards more livestock-based outputs went hand-in-hand with a more homogenous cropping structure (Springmann et al., 2018). During the last decades, the concentration on fewer crops, particularly those that are of high economic value for farmers arguably leads to less dietary diversity and potentially threatens domestic food security by reducing nutritive content in production.

Moreover, most farms in China continue to be very small, and rely predominantly on labour-intensive production strategies with little scope for mechanization. Recently, with labour cost increasing, labour-saving and capital-intensive production gradually reduced the reliance on family labour on many of the small farms (Otsuka et al., 2016). Furthermore, conventional monoculture agriculture depends on pesticides, fertilizers, and mechanization for higher yields, but this can translate into pollution, the loss of agrobiodiversity, and degradation (Grau et al., 2013). Unfortunately, the lack of consistent data at fine spatial and temporal scales has thus far limited long-term assessments of patterns, determinants, and causes of longer-term changes in land use extent and agricultural intensity for the whole of China.

Besides, food production tends to become more homogenous with a higher proportion of croplands devoted to the cultivation of wheat, rice, maize, and other high-yielding cereal varieties. These trends towards more similar compositions of food supplies also increase interdependence among countries and reliance on food trade (Khoury et al., 2014). While this is arguably also true for China, the degree of concentration on fewer crops and the spatial as well as temporal patterns of this concentration remain elusive.

During 1980 to 2010, cropland coverage in China changed distinctly, with conversion to urban areas in the Northeast (the Huang-Huai-Hai Plain), Yangtze River Delta, and Sichuan Basin, while grassland in the northwest arid and semi-arid region and forest in the southeast hilly region were converted to cropland (Liu et al., 2014). This implies that regions highly suitable for agriculture tend to lose fertile croplands because of increasing population and rapid socioeconomic development.

In summary, agriculture in China has witnessed significant changes due to population growth, economic development, urbanization and globalization. Moreover, spatial heterogeneity and autocorrelation is obvious in agricultural land use change, and these

changes have varied across regions and time. To study the food security of China, we have to understand these changes in land use, including their patterns and drivers.

4. Data

Data are the basis of research. For this study, we collected an immense amount of data, including remote sensing and statistical data, ranging from national to regional. Therefore, the first step was necessarily data fusion, to merge them together to build up our own database—county-level panel data (data and data source are in appendix A I-2).

To get an overview of agriculture and agricultural land in China, we retrieved data from FAOSTAT (<http://www.fao.org/faostat/en/#data>) (FAO, 2019). In 2017, agricultural land, including cropland and permanent meadows and pastures, covered 4.83 billion ha globally, with cropland at 1.56 billion ha. Of that, 528.5 million ha of agricultural land is in China (11% of world total), with 135.7 million ha cropland (8.7% of world total) (A I-3). Cropland accounts for 26% of agricultural land and in China it increased by 29% since 1961. However, harvested area of total cereals did not change much during the last 60 years, but for each crop, the changes are obvious and different. Excluding potatoes, the harvested area of the other four crops increased globally, but in China, that of potato increased more than three-fold while that of soybean declined 27% amidst a four-fold global increase. The harvested area of rice increased 44% globally, but in China increased only 15%. Wheat area fluctuated globally (overall increase of 7%) and also did not changed much in China (overall decrease of 4%). Maize experienced the second-largest increase globally of 87%, and in China its increase soared to 179% (Figure I-1). Production and yield details are given in appendix (A I-4 and A I-5).

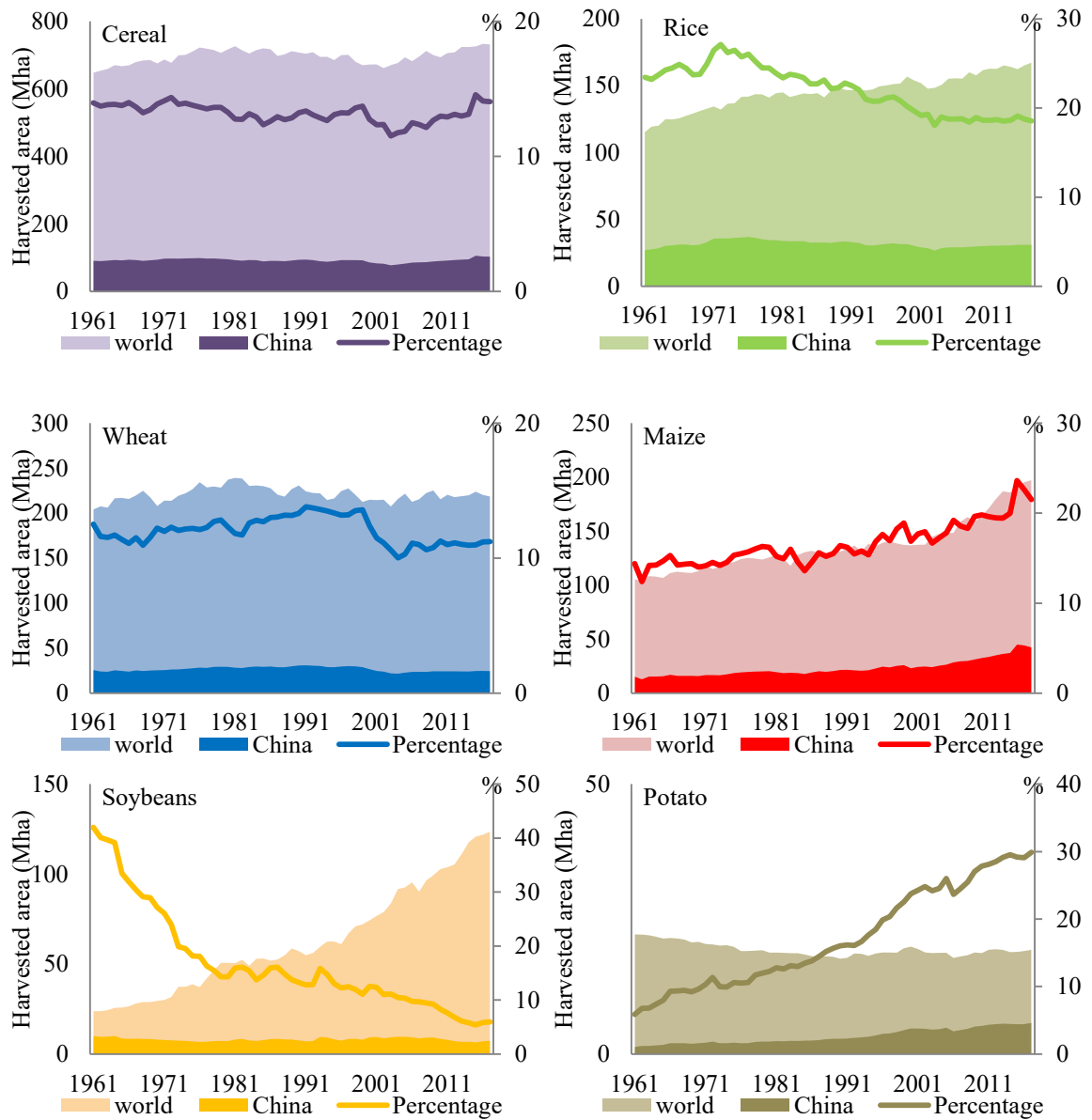


Figure I-1. The harvested area changes of cereal and five major crops in the world and China.

To get the cropland distribution (Figure I-2), we found land use raster data of China as interpreted by the Institute of Geographical Sciences and Natural Resources Research (IGSNRR, <http://www.igsnr.ac.cn>) of the Chinese Academy of Sciences (CAS), originally based on the digital images of Landsat TM/ETM. Cropland is mostly located east of Hu line—the population distribution line created by Hu Huanyong (Hu, 1990). In the northeastern region, there is chernozem that is black-coloured fertile soil containing a high percentage of humus and high percentages of phosphoric acids, phosphorus, and ammonia. This area is called the Northeast Plain, an important breadbasket for rice and soybeans. The middle-eastern region, including Hebei, Henan, Shandong, Anhui, Jiangsu, is a breadbasket for wheat, called the North Plain, or Huang-Huai-Hai Plain. There is another

main area for cropland distributed in eastern Sichuan, the southwestern China. It is called Chengdu Plain, where rice is the main crop.

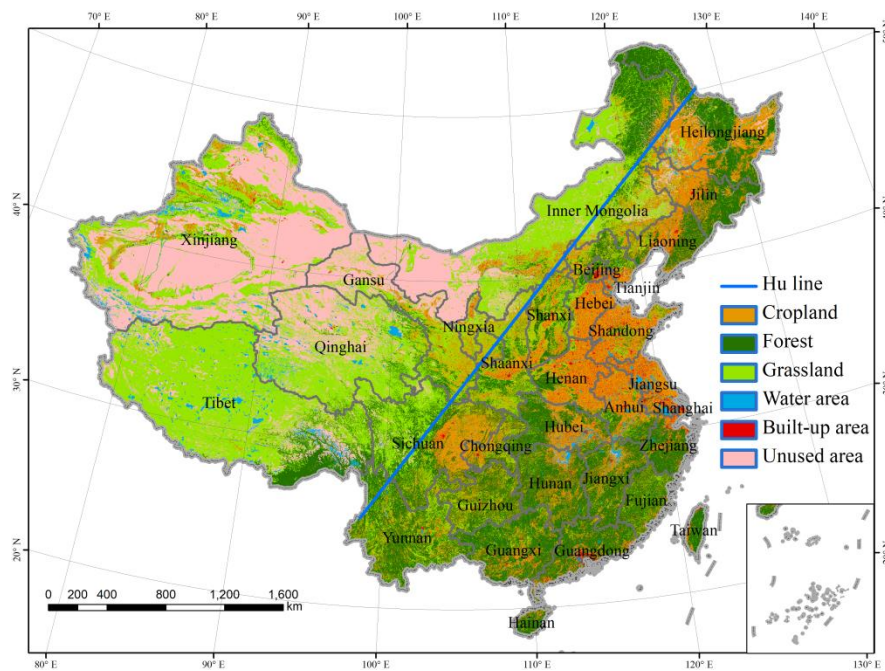


Figure I-2. Land use distribution in China in 2010.

Even though this land use data has a higher resolution, the time interval is 5-years and it could not be connected with specific crops. As a result, we compared the cropland of this data with the county-level statistical data (A I-6) and found that they had a well-correlated relationship, but cropland from remote sensing was larger than that from the statistics. We thought the reason could be that some low-quality cropland areas are transferred into equal-quantity cropland in unfertile regions. Finally, we decided to use the county-level statistical data for cropland and data related to crops, including harvested area, yield, and production. Besides these data, we also collected the climate, elevation and soil data for analysing the determinants.

5. Objectives, research questions and methodology

In this thesis, we used county-level panel data to develop a solid quantitative understanding of pattern, determinants, and causes of agricultural land-use trends across all of China from 1980 to 2011. The overarching aim of this thesis is to understand the spatial temporal patterns and determinants of cropland use changes and land use efficiency across all of China from 1980 to 2011. With a solid quantitative base, from the aspect of monitoring the patterns, constructing spatial determinant models, and evaluating land efficiency in crop production. To attain this goal, I structured my thesis into three research objectives, and

each is targeted to answer one particular research question. Each of the chapters has been published in or submitted to be published in peer-reviewed international journal. Together, this thesis should yield holistic, quantitative, and spatially and temporally explicit insights for all of China. These questions were answered using various kinds of spatial analysis, including exploratory spatial data analysis and spatially explicit panel regressions. Based on the results, we derived strategies and policies that may help to steer land use to more sustainable pathways. Specifically, we tried to derive spatially targeted policy recommendations that would concurrently enhance both provisioning and non-provisioning ecosystem services from land use.

The first objective of this thesis is to identify the hotspots of spatial concentration patterns in cropland. The second objective is to develop a quantitative model to clarify the determinants of its changes. The third objective is to investigate the changes in land use efficiency, and its determinants. Consequently, this thesis involved these objectives in three separate research questions:

Research Question 1 (Chapter II): What were the spatial patterns of changes in cropland area and major crops harvested area from 1980 to 2011?

To answer this question, we use Exploratory Spatial Data Analysis (ESDA) to describe the patterns. Spatial autocorrelation and semi-variance analysis map the spatial distribution, and identify local variability in land use data. Furthermore, an important aspect of dynamic graphics is the representation of data by means of multiple and simultaneously available types, so we construct tables, charts, histograms and plots, including stem and leaf plots, box plots, and scatterplots.

Research Question 2 (Chapter III): What were the determinants of changes in harvested area and yields of major crops?

Considering spatial heterogeneity and spatial dependency, we apply spatially explicit panel regression analysis. By comparing the statistical error rates, we assess different methods, including generalized least squares, spatial filters, wavelet revised models, and conditional autoregressive models, to select one with good performance. We then use the selected model to identify the indicators for agricultural land use changes and changes in the cultivated crops. With the same process, matching regressions are constructed to detect the causal effect of particular policy treatments on observed land-use changes.

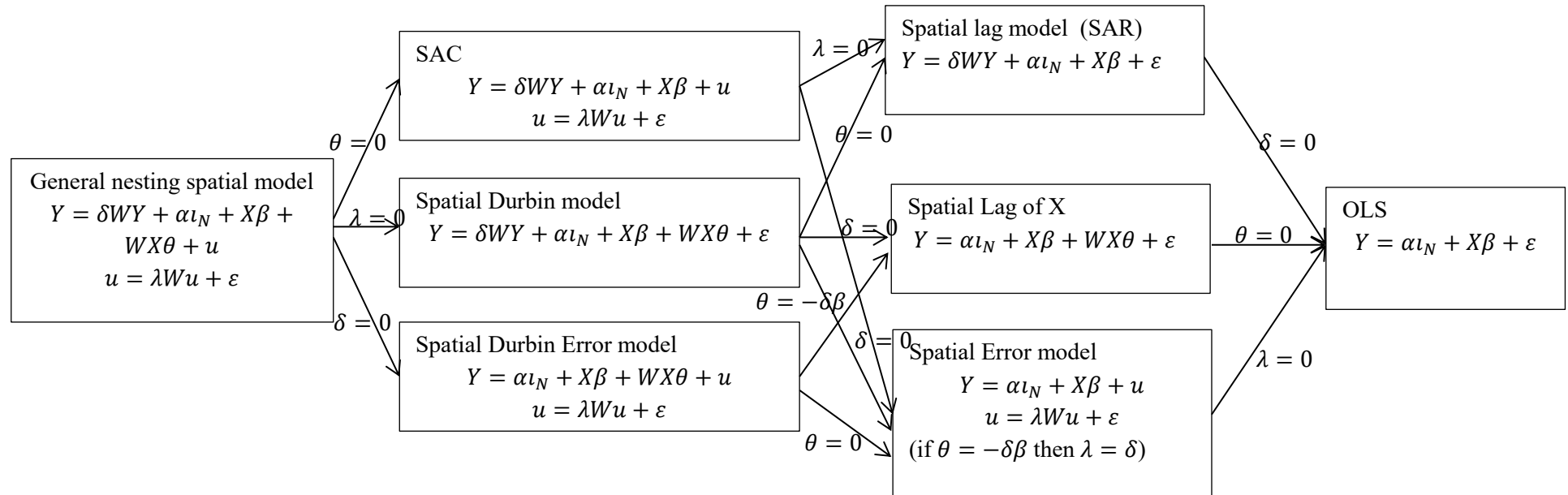
Research Question 3 (Chapter IV): What were the determinants for the observed changes in land-use efficiency and how do these vary across time and space?

Following the first two chapters, land-use efficiency is also analysed with a spatial model. We use the spatial autoregressive stochastic model (SAR-SFA) to estimate the TE of crop production and land use efficiency (LUE) in China at the county level from 1980 to 2011. This study aims to shed light on efficiency pathways by analysing how the TE of agricultural production varies spatially and temporally, paying particular attention to LUE.

Overall, we combined geographic and economic knowledge to improve the identification and analysis of abundant data. Additionally, using China as a case study, with county-level analysis for a long time period, is an important contribution to land use science.

Appendix I

A I-1. The relationships between different spatial dependence models for cross-sectional data.

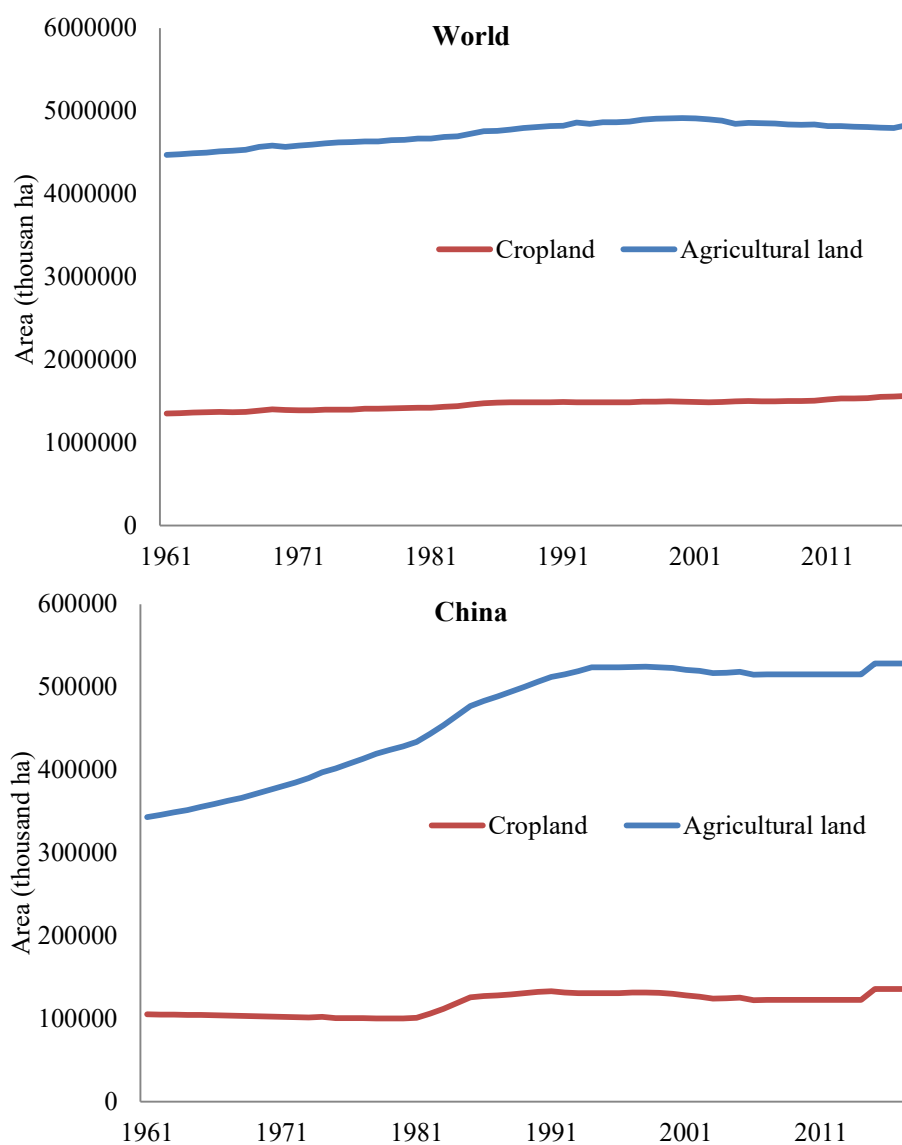


In general nesting spatial model, spatial dependence of y and x are both introduced. In this case, the parameters of δ , θ and λ are not zero, which δ is the parameter for the spatial dependence of explained variable y , θ is that for explanatory variable x , and λ is for the error term / unobserved variables.

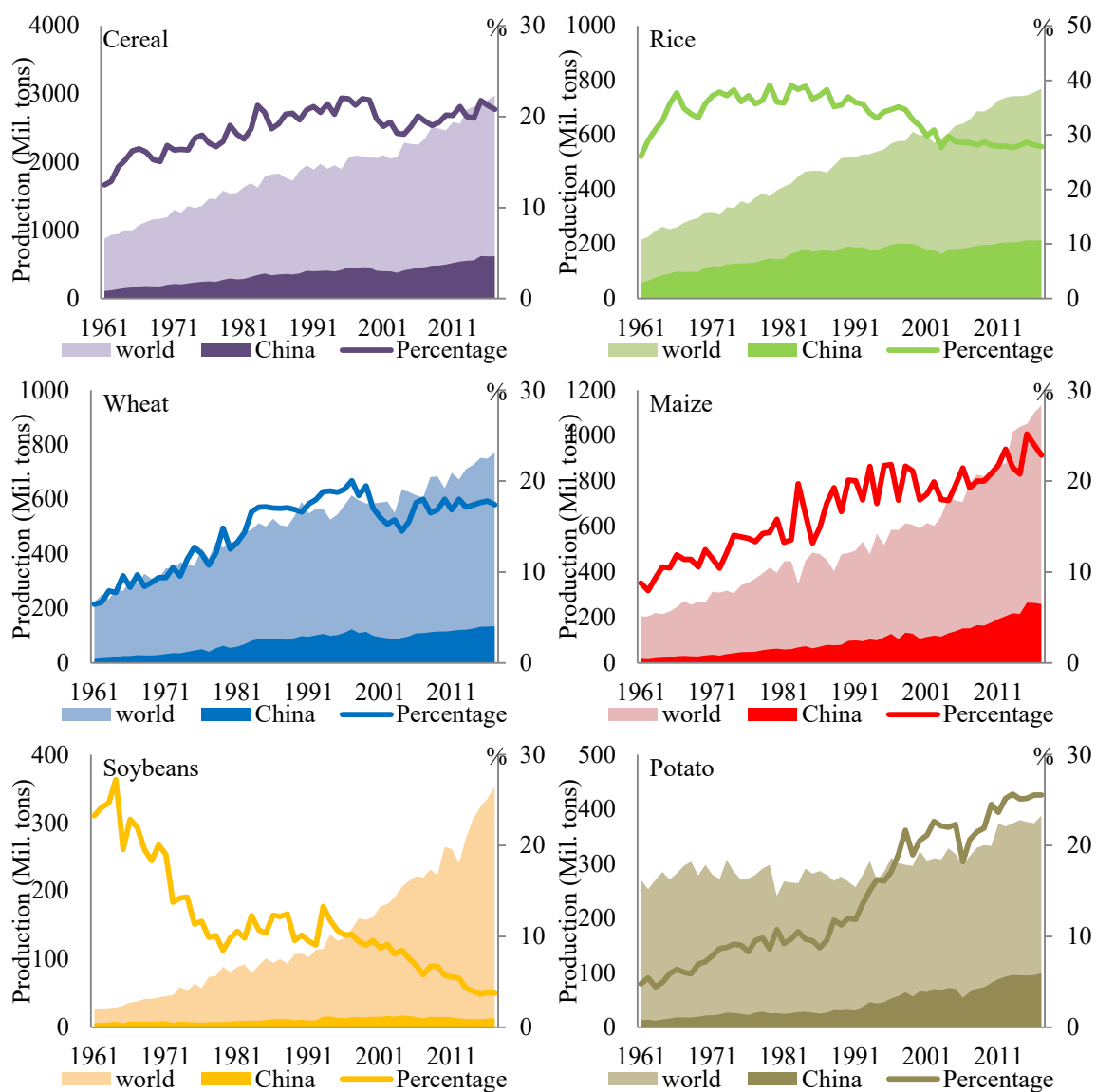
A I-2. Key datasets required for analysis in this study.

Data	Source and Website	Resolution
FAOSTAT 1961-2017	http://www.fao.org/faostat/en/#data	Statistic Data national
Land use in 1990, 1995, 2000, 2005, 2010	中国科学院资源环境科学数据中心 Center of Resources and Environment Data, Chinese Academy of Science http://www.resdc.cn/Datalist1.aspx?FieldTypeID=1,0	Raster 1km pixel
Statistic material for China from 1949 to 2009	60 YEARS OF NEW CHINA http://tongji.cnki.net/overseas/engnavi/YearBook.aspx?id=N2010030107&floor=1###	Statistic Data province
agricultural data from 1980 to 2011	http://tongji.cnki.net/kns55/index.aspx (1980-2010) yearbook: "The national agricultural cost-benefit data assembly"(2000-2012)	Statistic Data county
DEM	CHGIS, 2015, "CHGIS V5 DEM (Digital Elevation Model)", based on GTOPO-30 Data from USGS https://doi.org/10.7910/DVN/E1FHML , Harvard Dataverse, V8	1km pixel resolution
Climate: Mean, maximum and minimum of temperatures and Precipitation, Solar radiation (crop modeling needs may require more)	中国气象科学数据共享服务网 China Meteorological Data sharing service system http://cdc.cma.gov.cn/dataSearchForKWD.do?method=getInfo (1980-2010)	1 km pixel resolution
Soil and Terrain database for China plus additional information	ISRIC – World Soil Information, through the World Data Center for Soils (WDC-Soils) http://www.isric.org/data/soil-and-terrain-database-china	Vector

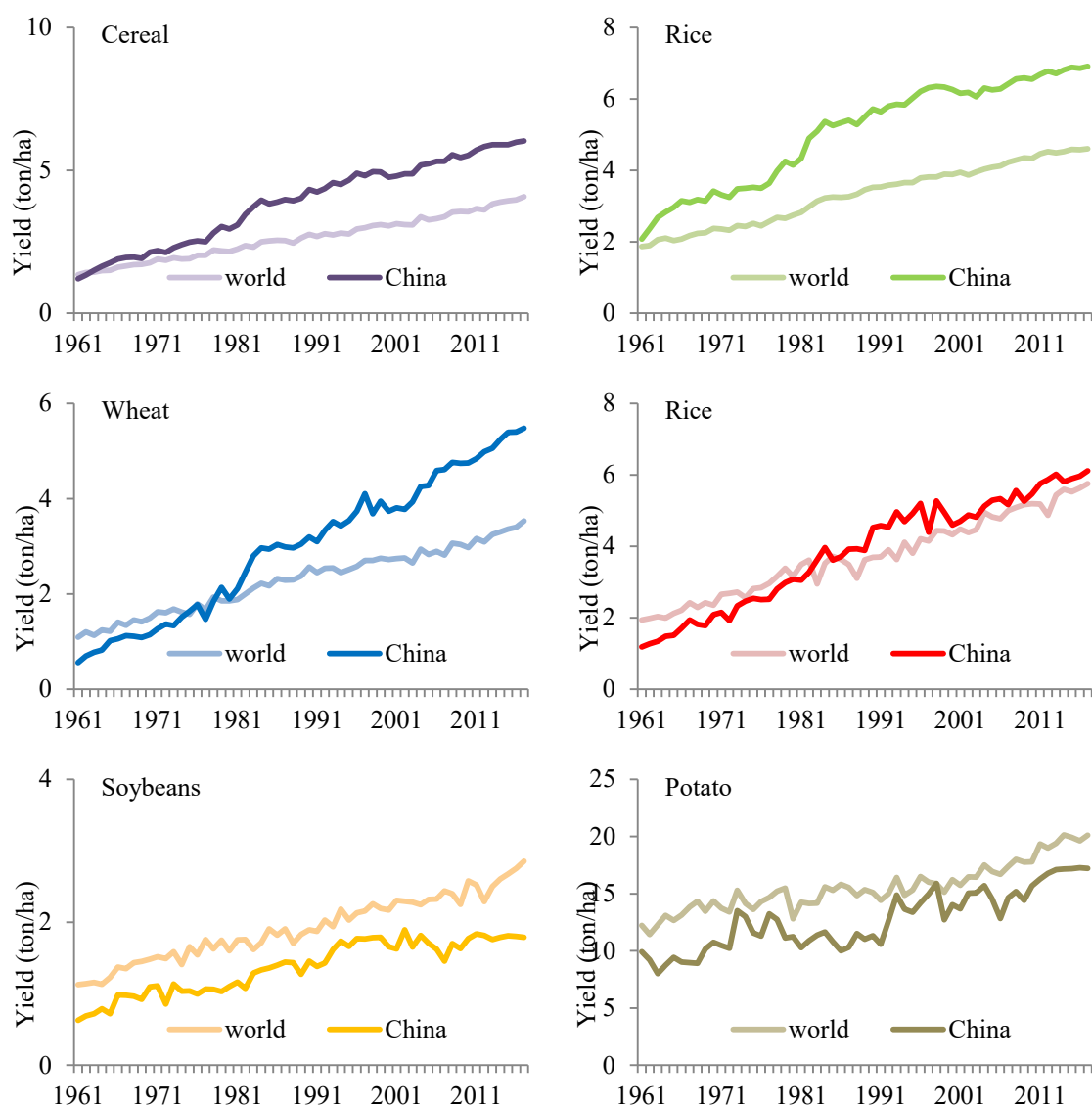
A I-3. Agricultural land and cropland in the world and China (sources from FAOSTAT 2019).



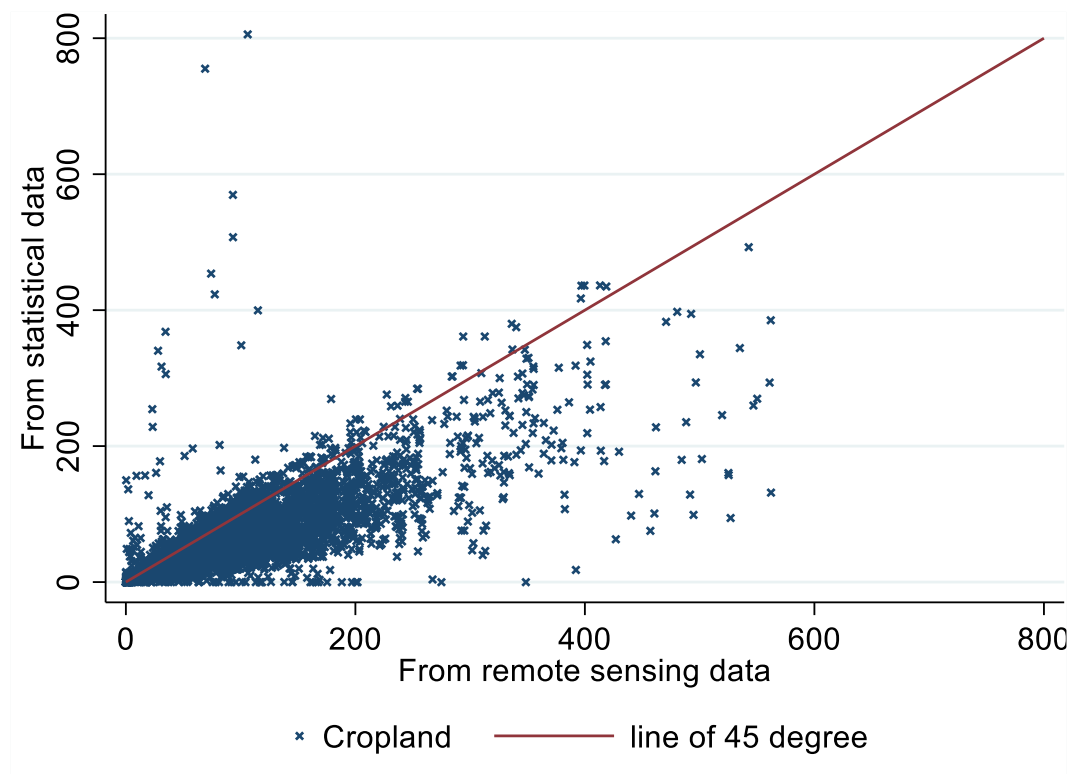
A I-4. Productions of cereal and five major crops in world and China.



A I-5. Yields of cereal and five major crops in world and China.



A I-6. Comparison the cropland data from remote sensing and statistics.



Chapter II. Cropland and major crops increasing concentration

(Co-authors: Zhanli Sun, Liangzhi You, Daniel Müller, published in Journal of Land Use Science in 2018, doi: 10.1080/1747423X.2019.1567838)

Increasing concentration of major crops in China from 1980 to 2011

Abstract

In many regions across the globe, crop cultivation is increasingly concentrated in suitable areas, such as those close to cities and areas with fertile soils. The concentration of crop cultivation can be measured in terms of spatial clustering and of inequality in the distribution of the cropland area. China has experienced substantial changes in the spatial configuration of its cropland during the past several decades, but few studies have quantified and mapped changes in spatial clustering and assessed the distribution of cropland area. We used official agricultural statistics at the county level ($N=2,354$) for each year from 1980 to 2011 for all of China to analyse the changes in spatial clustering and inequality of overall cropland and of the harvested areas of the five major crops (rice, maize, wheat, soybean, and potato). We quantified the spatial clustering with global and local Moran's I and assessed the inequality in the distribution of crop cultivation with the generalized entropy index. The results showed that the cropland area and harvested areas of the major crops indeed became more homogeneous over time. Moreover, we showed how the major crops concentrated in fewer areas and in the major historic breadbaskets that benefit from high land rents. Increasing concentration may offer opportunities in specialization and positive agglomeration effects but can reduce the resilience of food systems and agricultural sustainability due to increasing reliance on fewer crops and fewer places of production.

Keywords: land use, spatial clustering, spatial heterogeneity, crop production, Moran's I , inequality

1. Introduction

Global agricultural land use has transformed substantially in recent decades. One of the key changes was the concentration of production activities on fewer and more profitable crops (DeFries et al., 2015; Jepsen et al., 2015). Besides changes in farm structure and farm orientation, the global transformation of agriculture led to increasing concentration of agricultural land use around populated places and in areas with favourable natural endowments (fertile soils, favourable climate conditions, and abundant water resources). In short, spatial structures of commercially oriented agricultural land use are increasingly following the paradigms put forward by von Thünen and Ricardo (Alexander et al., 2015; Bren d'Amour et al., 2016a; Ricardo, 1817; Thünen and Hall, 1966).

David Ricardo showed that crop production attains higher rents in more fertile locations (Ricardo, 1817). Over time, populations are in increasingly concentrated densities in and around the areas suitable for crop production, which create further opportunities for agricultural growth, as these larger settlements act as major centres of demand. Positive externalities, such as those from knowledge and technology spill-overs, add force to the creation of spatial clusters around the fertile areas (Irwin and Bockstael, 2002).

Spatial clusters of crop production occur not only because of high Ricardian rents but also can emerge in surroundings of strategically established settlements, for example, at coastal ports or close to major trade hubs, as a result of low transport costs to these urban centres, in accordance with von Thünen's theory of land rent (Thünen and Hall, 1966). Recent evidence suggests that spatial clusters of crop production, particularly in developed and emerging economies, are increasingly polarized to fertile and accessible areas with good infrastructure, while much land in naturally less favoured areas and with lower quality of infrastructure is left abandoned (Kuemmerle et al., 2016).

While much research has focused on the patterns of spatial clustering of land use in general and on changes in the clustering of agricultural production in particular, less attention has been paid to the increasing spatial concentration of crop production among regions. However, evidence suggests that commercial agricultural land use is increasingly concentrated in fewer but highly productive areas, leading to a higher inequality of land use with a few producing regions dominating much of the output (Monfreda et al., 2008; Ramankutty et al., 2018). The concept of concentration, in this case, is akin to economic concentration, that is, an increasing share of the market is controlled by a shrinking number of firms. In terms of agricultural production, if only a few regions cultivate a large share of

a crop, then the cultivation pattern of this crop is highly unequal, regardless of whether these regions are located next to each other. The increasing inequality in agricultural production often reflects the process of regional specialization, facilitated by agglomeration of knowledge and skills in production and processing in a few pockets of production. Increasing productivity and higher efficiency in agricultural production archetypally goes in hand with higher specialization at farm and regional levels (Levers et al., 2018; Václavík et al., 2013).

Higher spatial clustering and increasing inequality in the distributions of crops are complementary concepts, although the two processes may share the same underlying drivers. Nevertheless, a high degree of spatial clustering does not correspond to high inequality and vice versa. High spatial clustering of a variable can be observed with fairly equal distributions among regions (i.e., small variance in terms of distribution), for example, when regions with a high share in the cultivation of a particular crop are next to each other. On the other hand, a few important producing regions may host a high share of the production of one specific crop (i.e., high inequality), but these few regions are not spatially connected to each other (i.e., low spatial clustering). Combined, the spatial clustering and inequality in the distribution of cultivation among regions can yield important insights into overall concentration of cropland use and crop production.

The concentration of agricultural production has important implications. Increasing specialization and spatial clustering of production can have manifold economic advantages, such as positive effects on agricultural productivity because of technology spill-overs and the emergence of service and knowledge centres (Brühlhart and Traeger, 2005; Fujita and Thisse, 2009). However, the increasing concentration on fewer crops and on fewer places of production may also infringe on domestic food security, bring higher production risks, and affect environmental conditions (Mehrabi and Ramankutty, 2018). The increasing concentration may also render countries and regions more vulnerable to production shocks, such as from crop diseases that spread more easily due to adverse weather events or in response to economic shocks, such as through price volatility (Bren d'Amour et al., 2016b). Therefore, an improved understanding of the degree and spatial locations of crop concentration and their changes over time is urgently needed.

China presents a good case in point with its dynamic land use changes in recent decades and its uneven distribution of cropland (Yu et al., 2018a). Only 15% of the territory of China is suitable for cultivation, which is mainly in the east of China (Liu et al., 2014). The

spatial patterns of cropland and especially crop production, however, experienced notable changes in China, particularly since the introduction of the household responsibility system in 1978, although the overall area of cropland did not change much (Liu et al., 2014; Liu et al., 2013; Xie and Liu, 2015). In many areas, particularly away from urban centres and in less fertile places, cropland has been abandoned since approximately the turn of the millennium due to labour emigration from rural areas, an ageing rural society, and less reliance on agricultural incomes (Frayer et al., 2014; Long et al., 2012; Xu et al., 2013). The degree of abandonment already jeopardizes the red line of minimum domestic cropland area, which was set by the Chinese government at 1.8 billion mu, equivalent to 120 million hectares (Li et al., 2015). Land use intensity was also reduced in many of the more marginal areas, witnessed among others by a reduction in the extent of multi-cropping (Yu et al., 2018a), leading to further reduction in harvested area. Another proximate cause for the reduction of cropland is the expansion of urban areas, which causes permanent loss of fertile cropland especially in economically developed regions, such as in the rapidly developing coastal areas in eastern and southern China (Bren d'Amour et al., 2016a). Finally, large-scale ecological conservation projects, such as the Sloping Land Conversion Program, contributed to the reduction in considerable amounts of marginal lands mainly in hilly and mountainous areas (Frayer et al., 2014).

At the same time, arable land increased in the northeast and southwest of China because of the expansion of irrigation facilities (He et al., 2015). Moreover, state and private investments into the agricultural sector have contributed to intensified land use in some areas. Agricultural production has shifted to higher yielding crops that are cultivated at high input intensities, especially in the country's main agricultural areas, and generate agricultural products with high value added (Xie and Liu, 2015; Yan et al., 2009; Yu et al., 2018a). China's accession to the World Trade Organization (WTO) in 2001 also influenced the crop structures and the spatial distribution of land use in China. A notable example is soybean production. Because of the lower yields, inferior oil extraction rate, and high production cost compared to genetically modified soybeans produced in the USA, Brazil, and Argentina, soybean production in China became less profitable after the accession to the WTO, and the harvested area of soybeans was reduced significantly.

National agricultural policies also play a critical role in shaping the spatial distribution of the crops. For example, the setting of a minimum purchase price on maize by the government to protect farmers' revenue led to rapid expansion of maize cultivation. Similarly, rapid growth of potato cultivation in recent years was caused by a national

support policy that promoted potatoes as a major staple food (traditionally only eaten as a vegetable by the Chinese, not as a source of carbohydrates). Many of these changes arguably led to an increasing polarization of land use, with higher concentration of profitable, highly intensive production in some areas, such as the concentration of vegetable production in Shandong and Hainan (Ji et al., 2018; Zhang et al., 2016). Nevertheless, it remains unclear to what degree and in which locations crop production has concentrated and how this concentration process evolved over time, especially at a fine spatial scale.

To improve the understanding of the evolution of cropping patterns, we analysed the changes in the spatial concentration of overall cropland area and of the harvested area of the main crops (rice, maize, wheat, soybean, and potato) using annual statistics at the county level for all of China from 1980 to 2011. We aimed to answer the following questions: How did the spatial clustering of all cropland and of the harvested areas of the five major crops change between 1980 and 2011? Second, how did the inequality of the distribution of harvested area of the five crops evolve between 1980 and 2011? The two research questions correspond to the two perspectives on concentration that we aimed to address, namely, spatial clustering and inequality of distribution in terms of cropland area and harvested areas of crops.

2. Materials and Methods

2.1 Data

We used county-level agricultural statistics from the China Compendium of Statistics, China statistical yearbooks, and various provincial statistical yearbooks (tongji.cnki.net/kns55/Navi/NaviDefault.aspx). These data are available for each year from 1980 to 2011 for all 2,354 counties of China. We extracted the area covered by crops (cropland area henceforth) and the harvested area for the five major crops that we defined as those crops with the largest harvested area in 2011, which were wheat, maize, rice, soybean, and potato. Note that when more than one harvest per year occurs on the same cropland, the harvested area may exceed the cropland area due to the multi-cropping. The data revealed the major agricultural areas of the selected five crops were in the northeast, north, and southeast (Figure II-1), which are also the areas that most rapidly urbanize and industrialize (for a map of the seven regions and the province names in China, see appendix A II-1). The spatial distribution of the five major crops in 2011 showed the

clustering of maize and wheat in northern and north-eastern China, rice in the northeast and the south, soybean in the northeast, and potato along the boundary of regions.

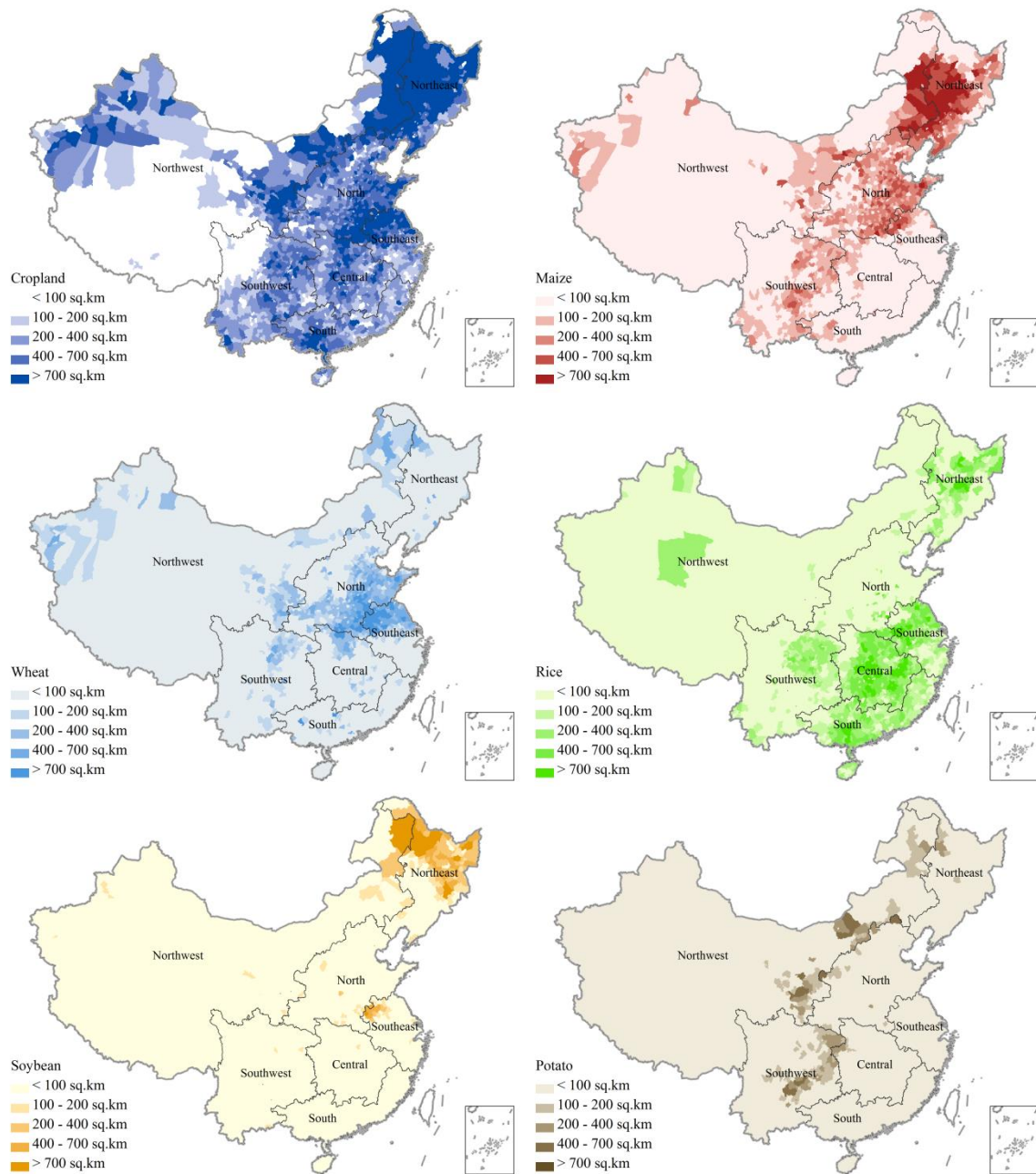


Figure II-1. Distribution of cropland and the five major crops in 2011.

2.2 Spatial Clustering

We quantified the concentration of land use from two perspectives, that is, spatial clustering and inequality of distributions of cropland and of the harvested areas of the five crops (Figure II-2).

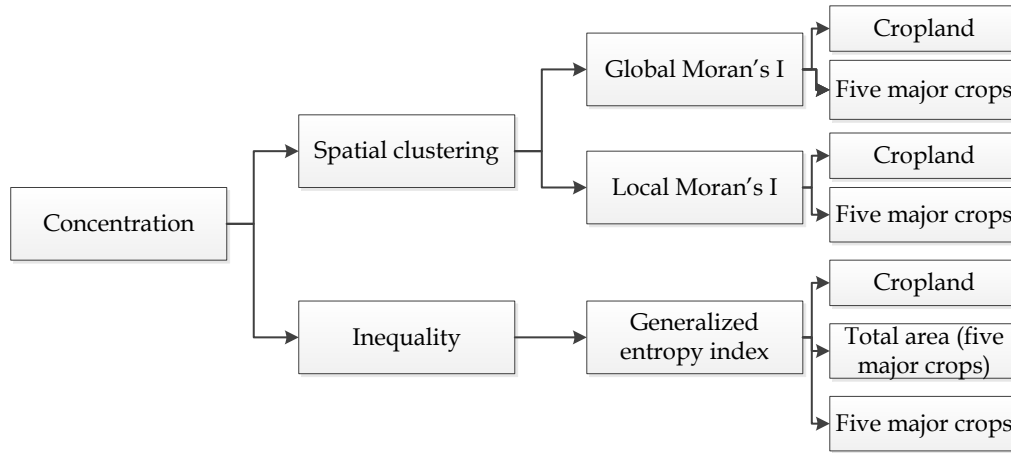


Figure II-2. Two perspectives on concentration and methods for quantification.

Spatial clustering is a frequent pattern of many geographic phenomena and an important justification for the use of spatial statistical analysis. We used Moran's I and local Moran's I to quantify the spatial clusters among neighbouring values. The Moran's I index is the extension of Pearson's correlation coefficient with a spatial weights matrix that defines the neighbourhood structure (Moran, 1950). Moran's I ranges between -1 and +1. Positive values indicate spatial clusters and negative values signal that neighbouring observations have dissimilar values.

The global Moran's I is a summary measure for the presence of spatial clustering across a study area, but the index cannot show where hot spots (spatial clusters of high values) and cold spots (spatial clusters of low values) are located. We captured local clustering patterns with local indicators of spatial association (LISA, Anselin, 1995), which visualize the spatial location of hot spots and cold spots on a map. Compared to alternative local measures of spatial associations, for example, Getis-Ord G_i^* , the local Moran's I can also identify spatial outliers, that is, when high values are surrounded by low values or vice versa.

We calculated the global Moran's I, and we mapped the local Moran's I for each year of our study period to reveal changes in the spatial clustering of the five crops and of the overall cropland area. We calculated the global Moran's I according to equation 1:

$$I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (\text{Equation 1})$$

where N , in our case, is the number of counties in China indexed by i and j ($N=2,354$); x is the variable to be investigated (cropland area and harvested area of the selected crops); \bar{x} is the mean of the areas in neighbouring counties; w_{ij} is a matrix of spatial weights with

zeroes on the diagonal (i.e., $w_{ij} = 0$ if $i = j$) and ones indicating the spatial neighbours. W is the sum of all w_{ij} . We settled on first-order rook contiguity matrix as the neighbourhood specification. We assessed the sensitivity of the results to the neighbourhood specification by carrying out identical calculations with a queen contiguity matrix and with a second-order rook matrix. The choice of the matrix did not change the results fundamentally, and the differences between rook and queen contiguity were, as expected, very minor (A II-4). For the sake of brevity, we only report the first-order rook case.

The LISA allowed mapping the local clusters. LISA were defined as:

$$I_i = z_i \sum_j w_{ij} z_j \quad (\text{Equation 2})$$

where z_i and z_j are deviations from the mean. A positive I indicates a clustering pattern, i.e., an entity and its neighbouring entities have similar values; a negative value for I indicates spatial outliers, i.e., an observation is surrounded by observations with dissimilar values. A permutation approach that yields pseudo significance levels using z-scores and p-values assessed the statistical significance of I . The permutation involves a random spatial assignment of all observations in the neighbourhood, as defined by the spatial weights matrix w_{ij} . The resulting distributions capture spatial randomness, which are then compared to the actual distributions (Anselin, 1995).

2.3 Inequality of Distribution of Cropland and Harvested Area of Crops

Inequality is measured several ways, with the most famous the Gini index and the Theil index (Lerman, 1984; Mussard et al., 2003). In this study, we quantified inequality with the generalized entropy index (GEI). The GEI is from the family of generalized entropy measures of which the Theil index is a special case. We preferred the GEI for our purposes because of its additive decomposability (e.g., by groups or by sources), which allows to attribute the individual contributions of groups to the overall inequality into within and between elements (Shorrocks and Wan, 2005; Shorrocks, 1984). In our case, decomposing the inequality of the harvested areas of the five crops combined into its components was useful to understand the contribution of each crop to total inequality. The GEI is defined as:

$$GEI = \begin{cases} -\sum_i f_i \log\left(\frac{y_i}{\mu}\right), c = 0 \\ \sum_i f_i \left(\frac{y_i}{\mu}\right) \log\left(\frac{y_i}{\mu}\right), c = 1 \\ \frac{1}{c(c-1)} \sum_i f_i \left[\left(\frac{y_i}{\mu}\right)^c - 1\right], c \neq 0, 1 \end{cases} \quad (\text{Equation 3})$$

where f_i is the population share of unit i , y_i is the considered variable's value of unit i , μ is the average of values of y_i , and c is a parameter that has to be selected. In our case, f_i was $1/N$ ($N=2354$) for the share of one county among the whole country, and y_i would be areas such as harvested areas of wheat, rice, maize, soybean, potato and the combined five crops. If $c=0$ or $c=1$, GEI becomes a special case, called the Theil index, where y_i needs to be strictly positive. Because some crops were not planted in certain countries in our study, which means y_i can be zero, we could not use the Theil index with $c=0$ or $c=1$. Therefore, we set $c=2$ following standard practice (Bellù and Liberati, 2006a, 2006b), which yields one half of the squared coefficient of variation, CV :

$$GEI(2) = \frac{1}{2} CV^2 \quad (\text{Equation 4})$$

where

$$CV = \frac{1}{\mu} \left[\frac{1}{N} \sum_{i=1}^N (y_i - \mu)^2 \right]^{1/2} \text{ and } 0 \leq GEI(2) \leq \frac{1}{2} (N - 1).$$

Since the logic of the decomposition by source is the same as in the case of the decomposition by subgroups, the GEI can be decomposed into individual contributions as follows:

$$GEI = \frac{1}{c(c-1)} \left[1 - \sum_j g_j \left(\frac{\mu_j}{\mu} \right)^c \right] + \sum_j GEI_j g_j \left(\frac{\mu_j}{\mu} \right)^c \quad c \neq 0, 1 \quad (\text{Equation 5})$$

where j refers to each subgroup, μ_j refers to the area share of group j , and GEI_j refers to the index in group j . The between-group component of concentration is captured by the first term $\frac{1}{c(c-1)} \left[1 - \sum_j g_j \left(\frac{\mu_j}{\mu} \right)^c \right]$: the level of inequality between groups. The second term $GEI_j g_j \left(\frac{\mu_j}{\mu} \right)^c$ gives the within group inequality. Theoretically, the GEI can range from zero to infinite, with zero indicating perfectly equal distribution and large values indicating high inequality. We calculated the GEI for every year of the study period to reveal the changes in the inequality distribution of cropland and the five crops among all counties of China.

3. Results

3.1 Spatial Clustering

Moran's I indices for cropland and for the harvested areas of the five crops were consistently above zero for each year from 1980 to 2011, indicating positive spatial clustering of county-level harvested areas (Figure II-3). The harvested area of wheat

exhibited the strongest clustering with a Moran's I close to 0.8 since 2000, followed by soybean and maize, all with modest increases in the spatial clustering. Cropland was less strongly clustered than the harvested areas of the individual crops, except for potatoes. In addition, cropland and the harvested areas of the individual crops except rice became more spatially clustered, particularly between 1980 and 2000 (Figure II-3). Since approximately 2000, no clear trends were visible, apart from the decrease in the clustering of the harvested area of potatoes.

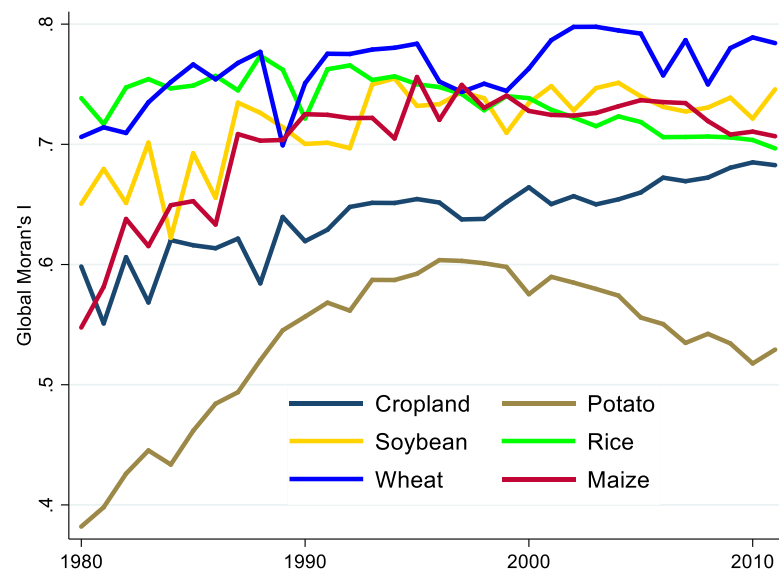


Figure II-3. Global Moran's I of cropland and five crops from 1980 to 2011.

Figure II-4 shows the LISA cluster maps for cropland in ten-year steps, and two prominent hot spots of cropland are clearly visible in northeast China (the Northeast China Plain) and in central east China (the North China Plain). These two areas have long been breadbaskets of China. The southern part of the North China Plain has been cultivated for over four thousand years and is widely regarded as the cradle of Chinese civilization. Over time, the clusters in northeast China expanded, while the hot spots in the North China Plain shrank in spatial extent. The two smaller hot spots in Inner Mongolia and around Ningxia (see A II-1 for a map with provincial names) also contracted. Unsurprisingly, cold spots were observed in west China (Yunnan, Sichuan, Tibet, and Qinghai) and in the hilly areas in the south (Zhejiang, Fujian, Guizhou, and Guangxi) due to less favourable natural endowments and higher emigration rates from rural areas. The low-high outliers (counties with low values surrounded by counties with high values) were mainly located on the peripherals of the hot spots in northeast China and Inner Mongolia. The high-low outliers (counties with high values surrounding by counties with low values) were mainly located in southern

China, where basins and small plains in the hilly regions often have high shares of cropland area, while their neighbours have low shares of cropland.

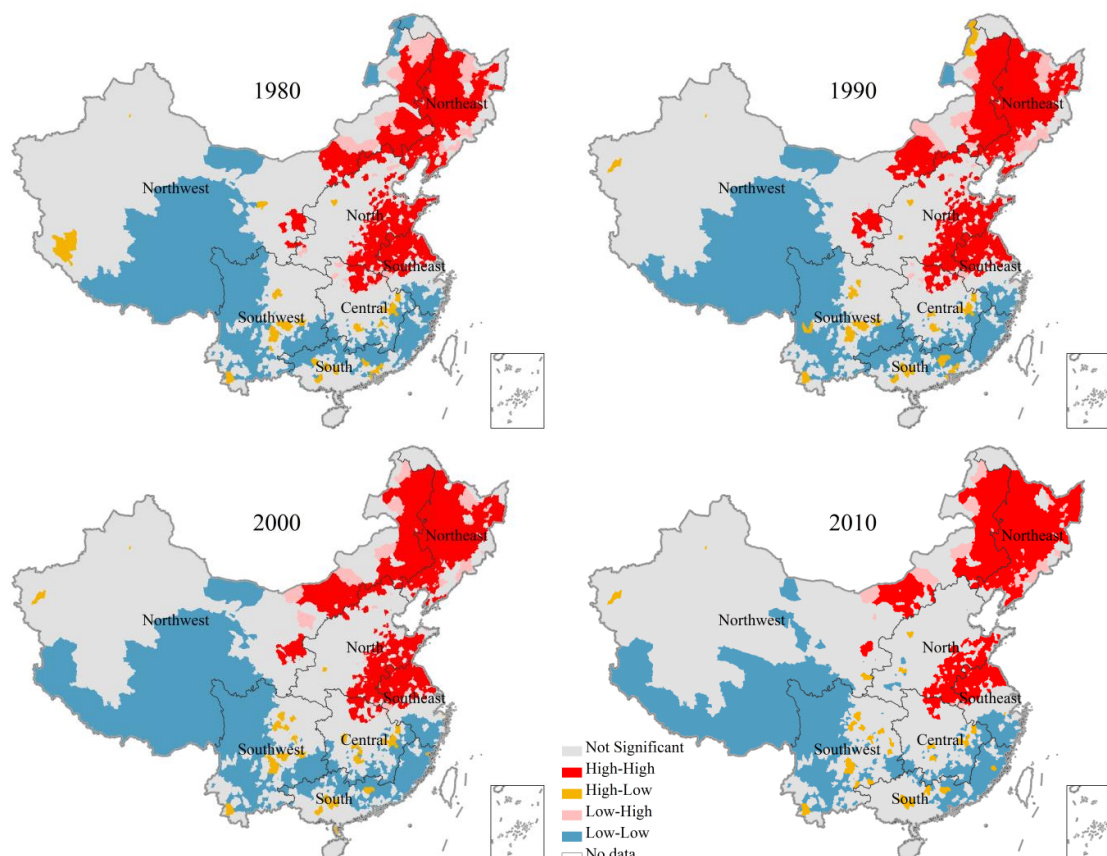


Figure II-4. LISA cluster maps for cropland area from 1980 to 2010 in 10-year intervals (High-High, indicates hot spots; Low-Low, indicates cold spots; High-Low and Low-High, indicate outliers).

We calculated the local Moran's I for the harvested areas of the five major crops over the study period and for each year from 1980 to 2011. Because of space limits, we take maize as the example to present our results (Figure II-5; results for the other crops are found in appendix A II-2.). From Figure II-5, the harvested area of maize in 1980 clustered in a diagonal belt stretching from southwest to northeast and sandwiched between two cold spot zones, one stretching from Tibet to Inner Mongolia in the northwest region and one that covered much of south, central, and southeast China. In subsequent time steps, the hot spot belt substantially contracted, particularly in the hilly areas of the southwest where it had already disappeared by 1990. The maize hot spots increasingly concentrated in Inner Mongolia, the northeast and north China. Figure II-5 also shows a contraction of the cold spot belt in the northwest, while the large cold spot in south-eastern China remained largely intact.

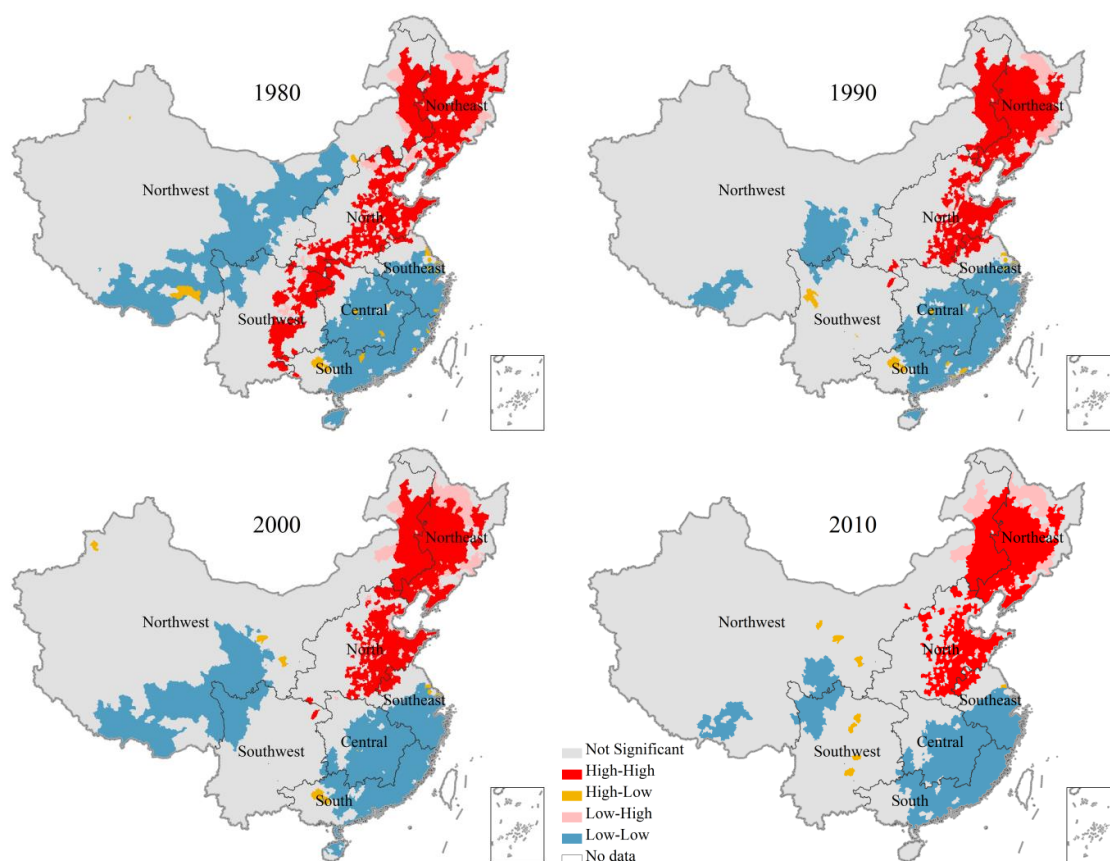


Figure II-5. LISA cluster maps for harvested area of maize for 1980, 1990, 2000, and 2010.

3.2 Inequality of Distribution of Cropland and Harvested Area of Crops

Figure II-6 shows inequality trends for cropland and for the harvested areas of the five major crops. Figure II-6a reveals that all cropland was distributed fairly equally (low inequality), implying few changes in the overall distribution of cropland among counties. In contrast, inequality of the harvested areas of the five major crops consistently increased. Soybean was the most unequally distributed and had the largest increase in inequality, suggesting that the area harvested with soybeans was concentrating in ever fewer counties. The increasing spatial clustering of soybean in northeast China corroborated this result (shown in A II-2.d). Potato cultivation was also unequally distributed in China, with a rise in inequality since 1990, as measured by the GEI. The other three crops were more equally distributed and showed less obvious changes over time.

The inequality in the distribution of cropland and harvested areas of crops is shown in Figure II-6a. The GEI of the total harvested area of the five crops increased rapidly after 2000 (shown by the cumulative amount of the GEI in Figure II-6b). Note that the GEI of the total area of the five crops was not equal to the average of the GEIs of the five crops; rather, the GEI of the total area of the five crops was decomposed and attributed to individual crops based on the individual GEI values together with harvested areas as

weights (see Methods section). From the decomposition of the GEI in Figure II-6b, rice and wheat accounted for more than 60% of total inequality before 2000, while the contribution of maize increased steadily from 11 to 48%. In contrast, the contribution of rice to total inequality declined by 15% from 1980 to 2011, mostly because of total area changes in rice and maize. In addition, the rising inequality of soybean contributed to the overall rise in the inequality of crop cultivation, although the overall contribution of soybean was low due to its relatively small harvested area.

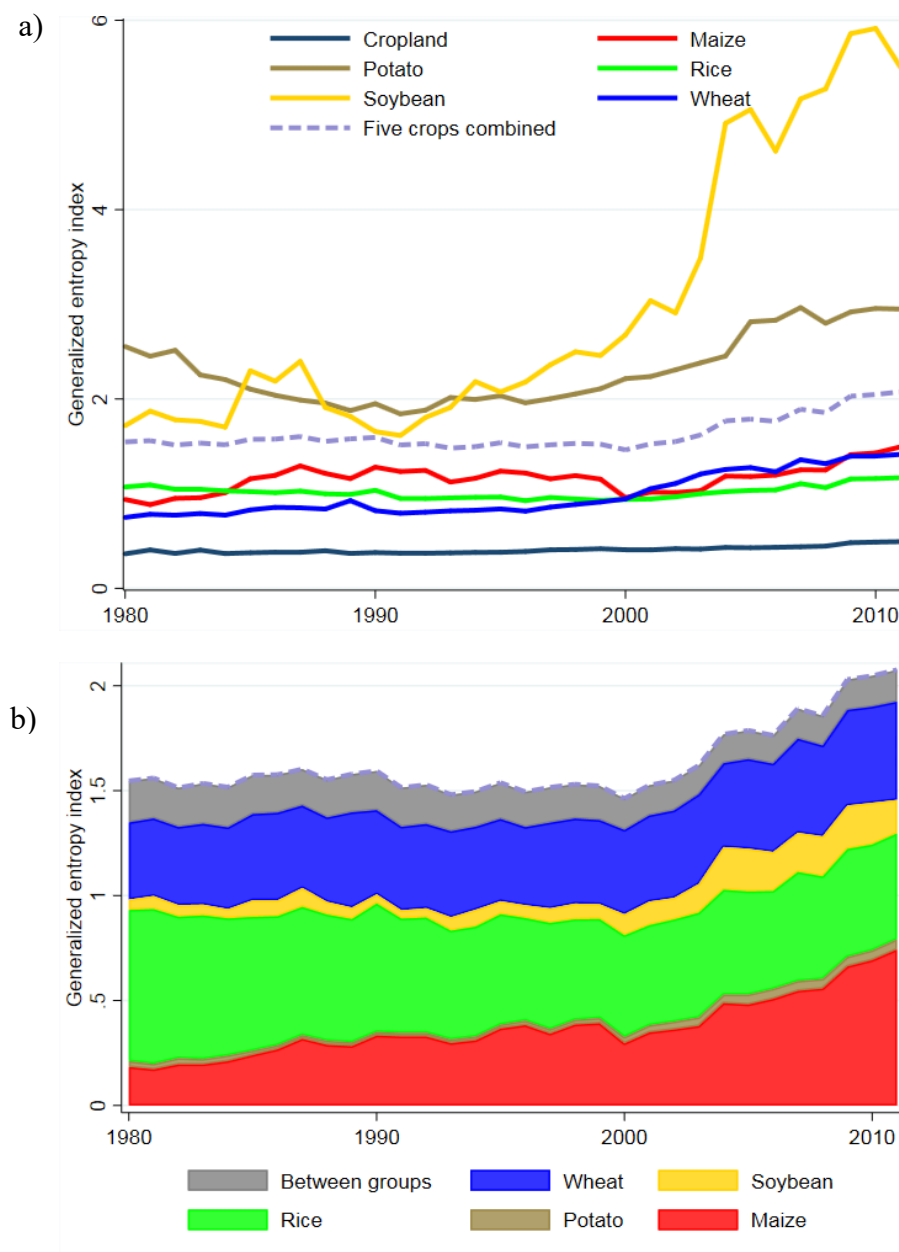


Figure II-6. Generalized entropy index for cropland and for the harvested areas of the five selected crops (a) and decomposed harvested area of the five crops with the sum indicating total inequality (b).

4. Discussion

Our study revealed that the cultivation patterns of the major crops in China became increasingly concentrated between 1980 and 2011, albeit the increase in concentration has been small for some (e.g., rice) and larger for other crops (e.g., soybean). Even though a high spatial concentration may be beneficial for more profitable agriculture, a decrease in crop diversity can bear negative consequences, such as increased susceptibility to diseases and pests and vulnerability to weather shocks (Li et al., 2009; Sheng et al., 2017). Conversely, since overall cropland has been controlled under many of China's agricultural policies, including initiatives to maintain the red line of 1.8 billion mu (i.e., 120 million hectares) of cropland (Long, 2014), the development of all cropland was much less dynamic but still showed some tendencies of concentration.

The global Moran's I revealed increasing spatial clustering, particularly in the period from 1980 to 2000 and for wheat, maize and soybean but less so for rice and potatoes. Possibly, many of these changes towards increased concentration were brought about by the transition from a centrally planned to a market-oriented economy, which facilitated the gradual transition to more commercial-oriented farming starting in the early 1990s. During the transition, farmers were able to choose which crops to produce (and typically selected the most profitable ones) and were able to purchase agricultural inputs on the markets. For example, the spatial clustering of rice decreased since the early 1990s because farmers in hilly areas in the south increasingly diversified and converted rice paddies, in particular on sloping land, to higher-value and labour-saving crops (e.g., tea, fruits); hence, the area harvested by rice was reduced (Yu et al., 2018b). At the same time, rice production increased in northeast China due to the higher quality of rice in the region, which stimulated more market demand and thus higher price premiums.

Potato is not only a staple food for hundreds of millions of people but also a cash crop. The increase in the spatial clustering of potato can be explained by the increasing contribution of returns from potato production to households as altitude increases. However, the spatial patterns of potato cultivation correlate not only with agroecological site conditions but also with poverty, which tends to be higher in the hilly and mountainous areas. Likely, potato cultivation will further expand in the future in response to national policies that promote potatoes as a major staple food. Nevertheless, the level of spatial clustering in potatoes was still lower than that of other crops because potatoes are more insensitive to soil and climatic conditions.

We showed that crop production in China increasingly clustered towards fewer core cultivation zones. These zones were characterized by high natural suitability for agriculture and by beneficial market access (Li et al., 2017; Weinzettel et al., 2013). They were located to the east of the so-called Hu Line (A II-1), where most economic output concentrates and where more than 90% of the population resides (Hu, 1990). This region is where the earliest traces of agricultural cultivation have been found in China (Yang et al., 2015). Interestingly, the cultivation of the major crops seems to increasingly concentrate in these cradles of Chinese agriculture. The economic transition, from a largely agricultural country to one where an increasing share of the workforce is employed in industry and in the service sector, has been a key underlying driver for the increasing concentration of the cultivation of major crops to the east of the Hu line. In addition, some of these regions (e.g., the north China plain and northeast China plain) have more suitable topography for the use of machinery and thus attract investments into capital-intensive agricultural intensification.

China's government postulated self-sufficiency in grain production in 1995 (Brown, 2012) and heavily subsidized grain production since then (Huang et al., 2011; Li et al., 2014). These subsidies focused on the important grain production regions, i.e., the abovementioned plain areas. As a result, major grain crops are increasingly concentrated in these regions. In contrast, rural areas, where profitable agriculture is compromised by difficult topography, low fertility, or adverse market accessibility, increasingly lose out because of emigration of the workforce in search of better income opportunities and the associated ageing of the rural population that are left behind. Nature conservation policies, such as the Sloping Land Conversion Programme, reinforce this development by encouraging the retirement of marginal land from agricultural production. However, some centres of intensive agriculture disappeared from the local cluster maps (Figure II-4). For example, the Sichuan basin, the most important agricultural region in western China, disappeared from the hot spot maps of the major crops, especially for the case of maize (Figure II-5). The Sichuan basin is very densely populated and characterized by extremely small farm sizes. Most agricultural production focuses on crops with high value added, such as vegetables and fruits, and on intensive livestock production.

Our analysis on inequality revealed rising inequality of cropland and of harvested areas of the five major crops, albeit only slightly for most crops except soybean. Hence, crop cultivation was increasingly concentrated in fewer counties, irrespective of changes in the size of the harvested area. For example, the inequality of harvested area of soybean soared

after 1995, while the total harvested area of soybean decreased during this period. The increasing globalization of agricultural production mainly caused the dynamics in the concentration of harvested areas of soybean. China became member of the WTO in 2001. Since then, the Chinese demand for soybean skyrocketed, mainly to meet protein consumption of the growing monogastric livestock numbers. By 2011, soybean imports satisfied 70% of total soybean consumption (FAO, 2015), because soybean imports from the large farms in the Americas achieve far higher profit margins than those of Chinese soybean producers (Sly, 2017; Song et al., 2009). The decomposition of inequality (Figure II-6b) illustrated that maize became the preponderant crop for the growing overall inequality because of the increase in its harvested area share over the five major crops combined and because of increasing domestic demand and rising prices for maize as a feed source for livestock (Meng et al., 2006).

Subnational statistics on agriculture in China may not convey the complete truth due to inaccuracies in measurement and biased reporting (Gale et al., 2002). As a result, the spatial patterns that we revealed for the five main crops and for overall cropland may bear considerable uncertainty. Moreover, we were not able to examine the diversity of less important crops with lower harvested area, because data for these crops frequently suffer from missing values and high measurement inaccuracies. While most previous assessments had to rely on provincial-level data, we relied on county-level data with much higher spatial resolution. However, the scale of our analysis remained coarse. Unfortunately, national crop maps that rely on wall-to-wall remote sensing imagery are, to the best of our knowledge, not available to date. Such maps would provide a better database for more accurate assessments of the concentration patterns of China's agricultural production.

5. Conclusions

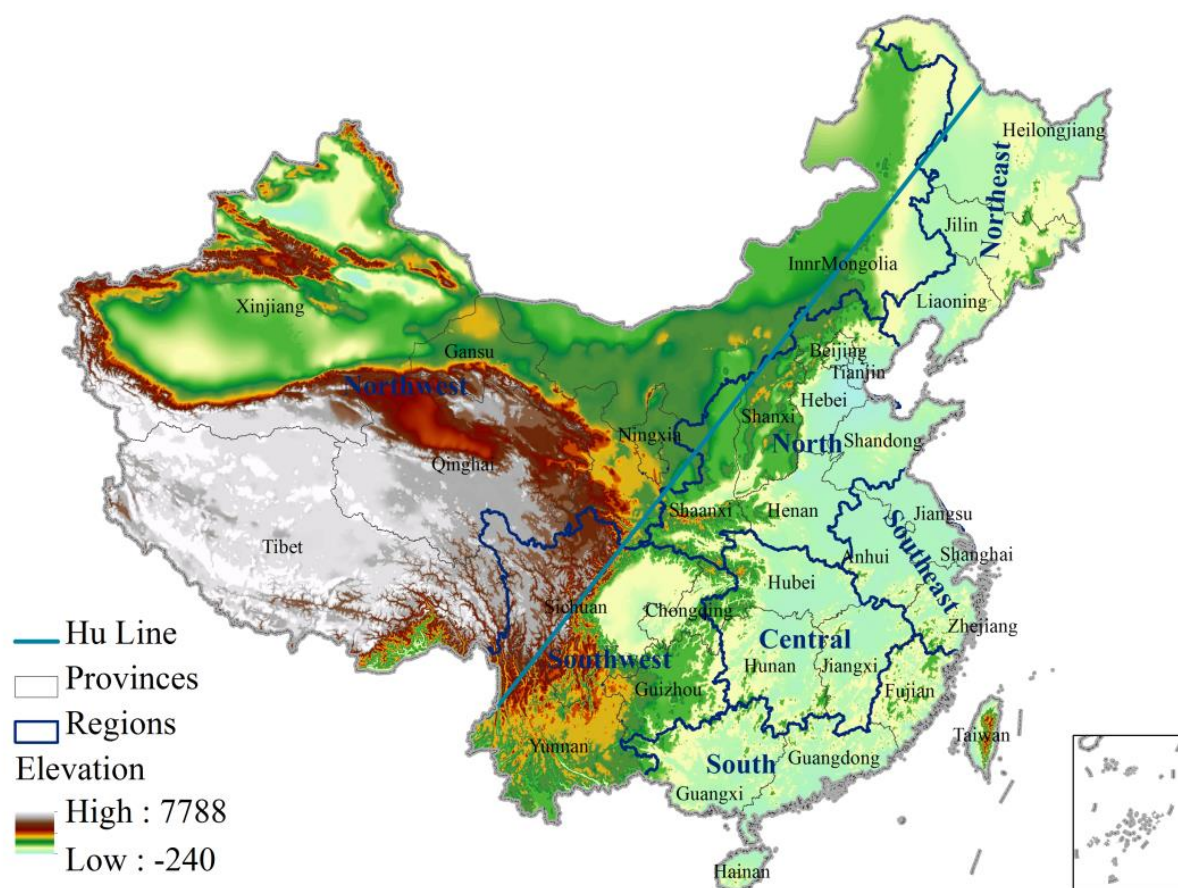
Crop production in China became increasingly concentrated in terms of its spatial distribution since 1980. All cropland and the harvested area of the major crops gradually concentrated in the major historic breadbaskets of eastern China, especially since 1990. Maize and soybean changed most dynamically since 1990, with both increasingly unequally distributed, despite diverging trends in their harvested areas that substantially increased for maize but decreased for soybean. Agricultural policies, such as the rural land reform, changes in trade patterns, and nature conservation policies as well as changing

domestic diets all played an important role in shaping the spatial clustering and inequality among crops and in the overall concentration of cropland.

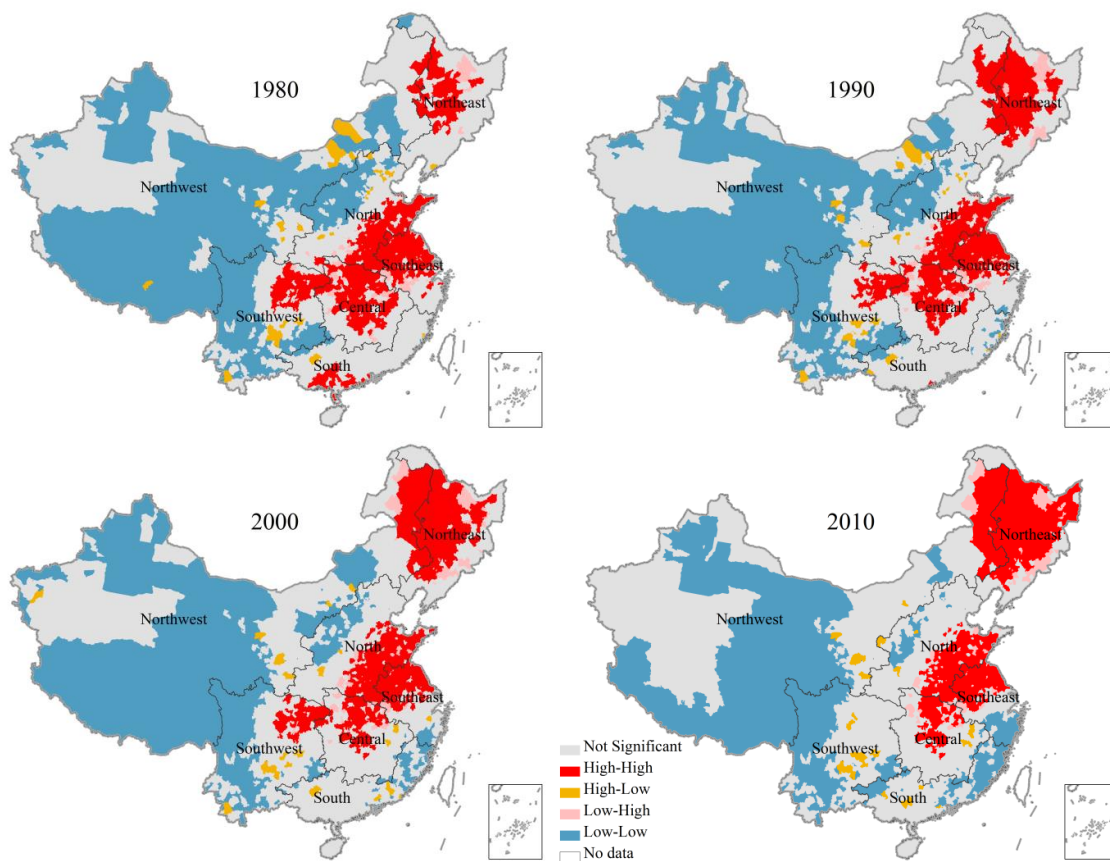
The increasing concentration can have positive effects on crop productivity through effects of technology spill-over, processing facilities, and knowledge. In addition, with the increasing concentration, the recovery of nature may benefit in areas where crop production contracted in terms of area used and of cultivation intensity. However, a higher concentration of production of major staple crops may also lead to higher vulnerability to climate change, natural hazards, and disease outbreaks. This research revealed the complex dynamics of the spatial concentration in cropland and major crops with the example of China, and we envision these results to foster the implementation of mitigation measures that reduce agricultural production risks and increase the resilience of the agricultural production system.

Appendix II

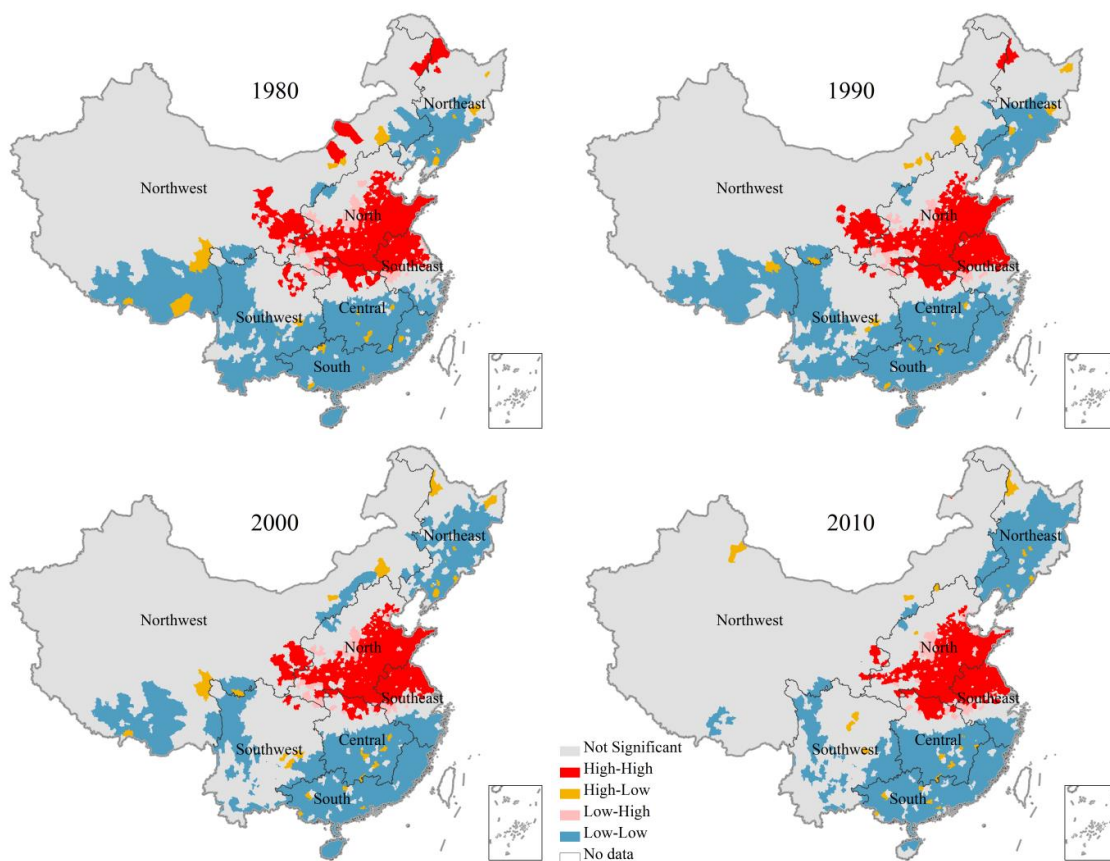
A II-1. Counties, provinces, and regions of China.



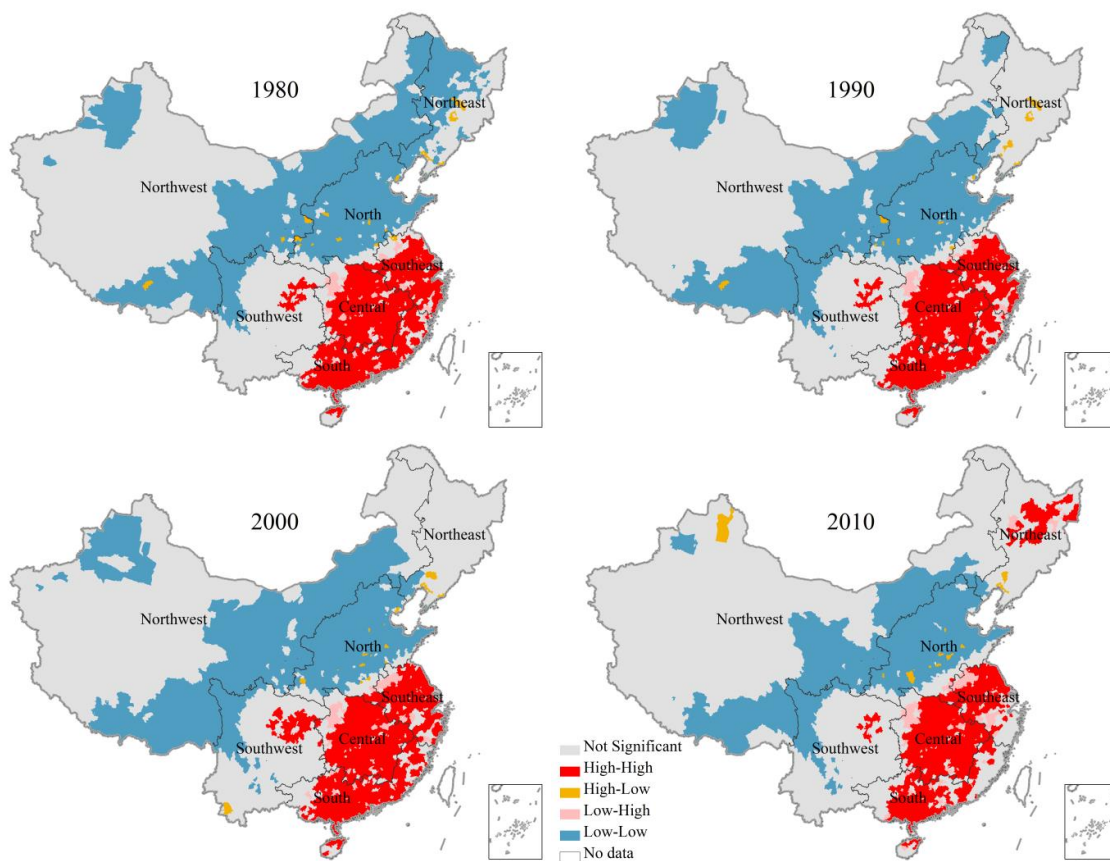
A II-2. LISA maps of harvested areas of crops.



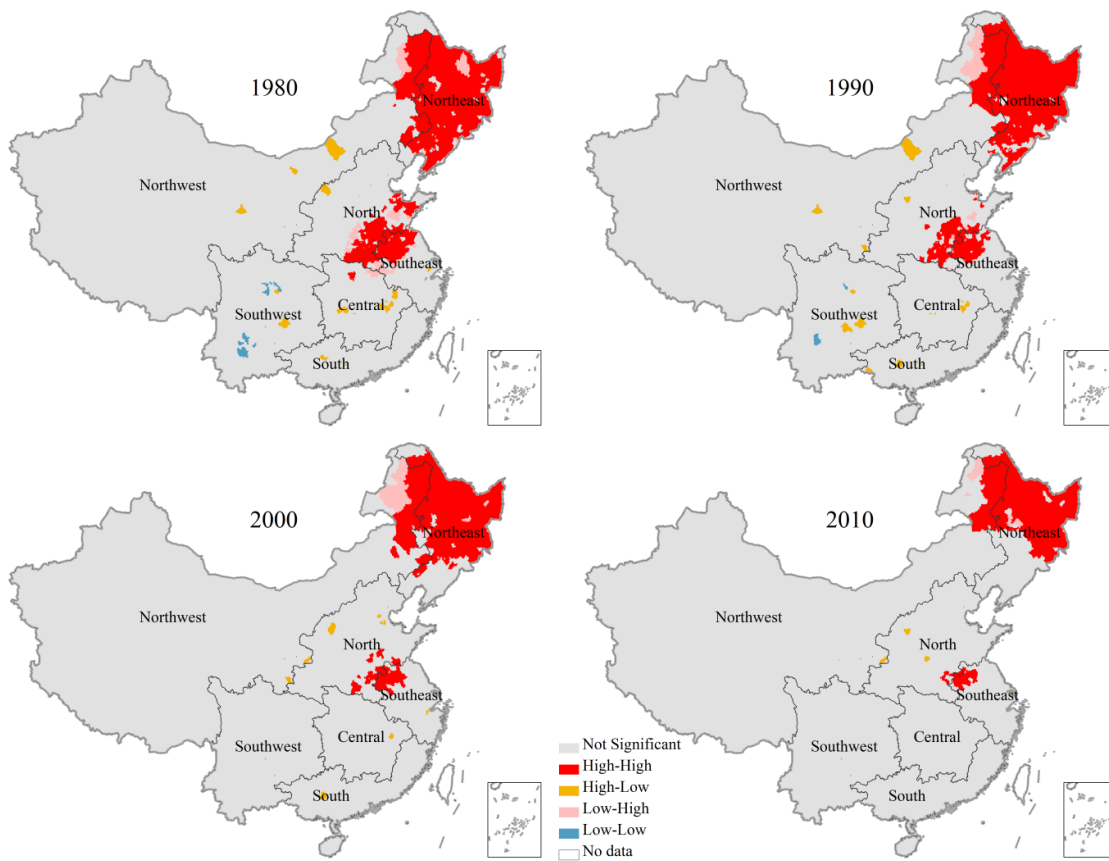
a. LISA maps of harvested area for all five crops combined.



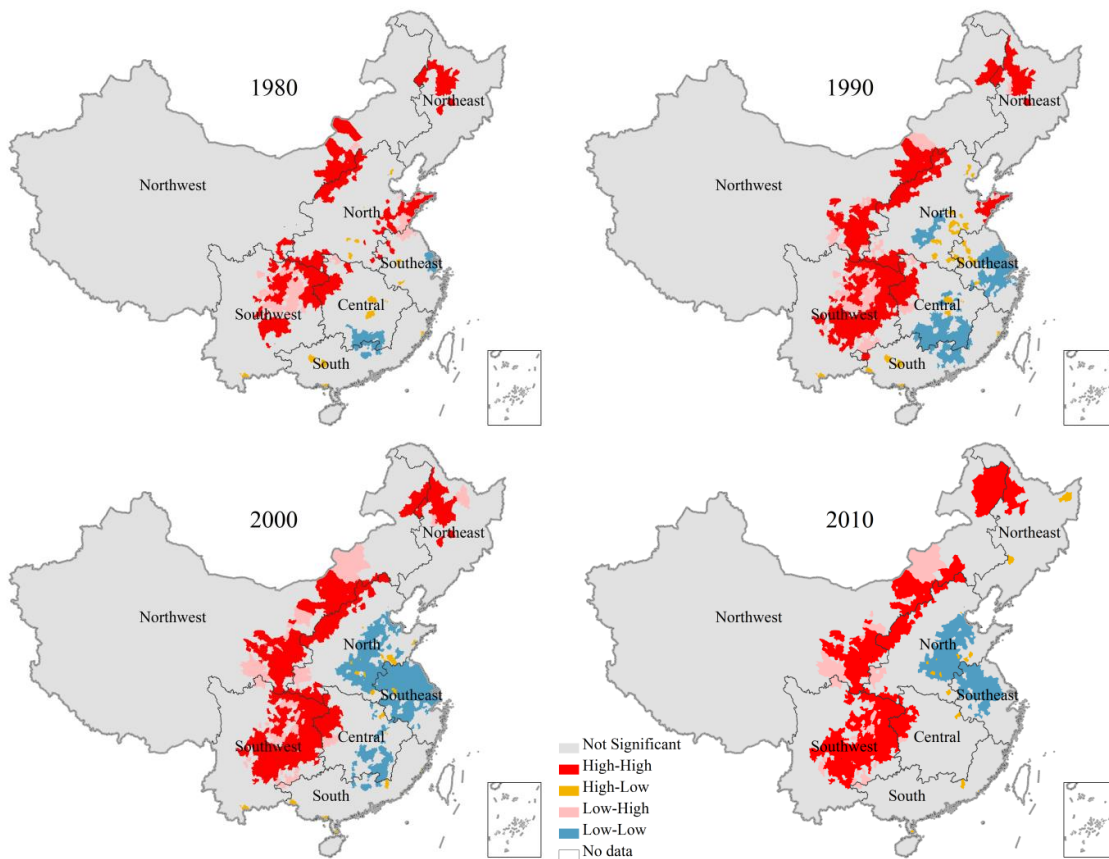
b. LISA maps of harvested area for wheat.



c. LISA maps of harvested area for rice.

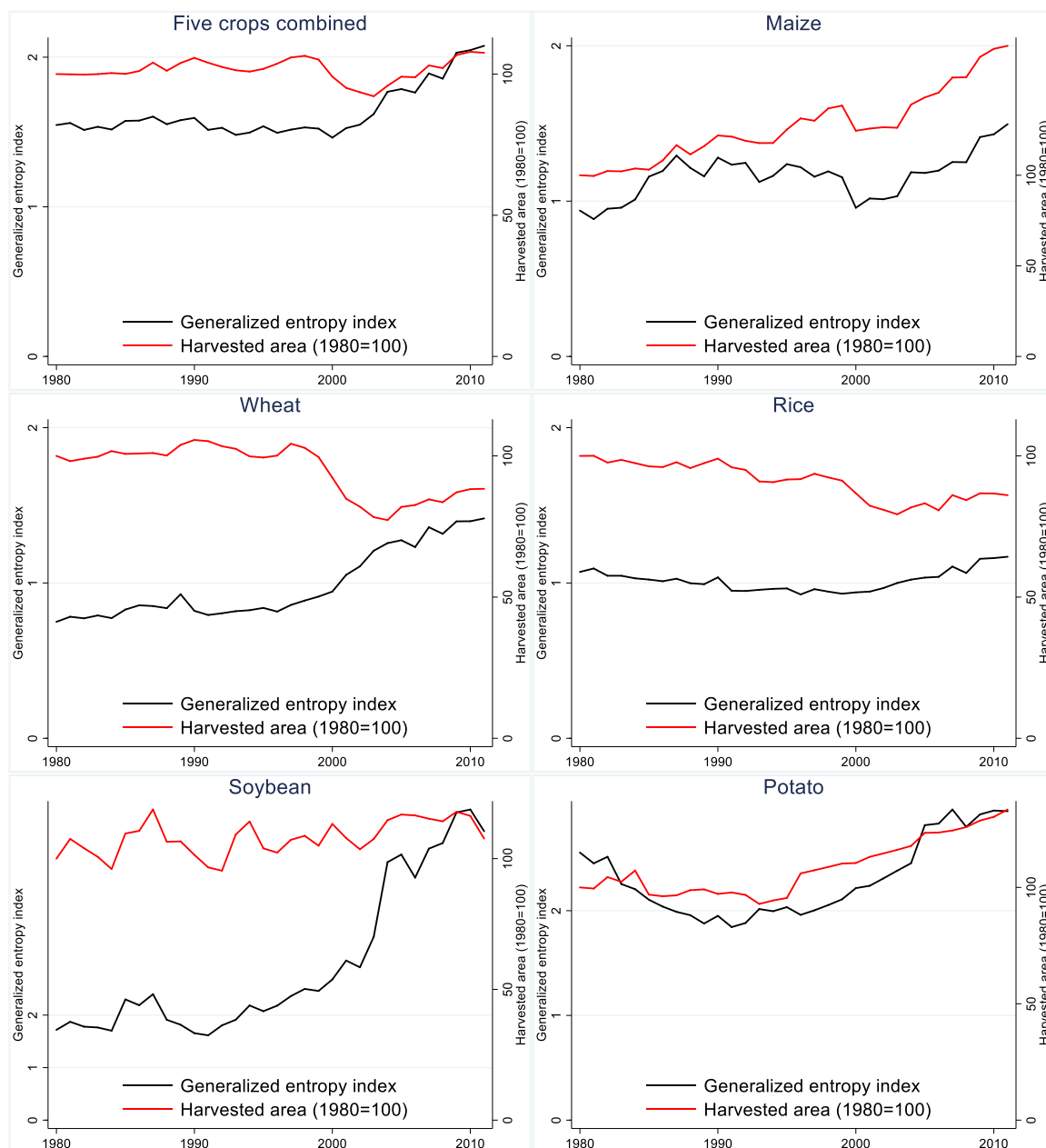


d. LISA maps of harvested area for soybean.

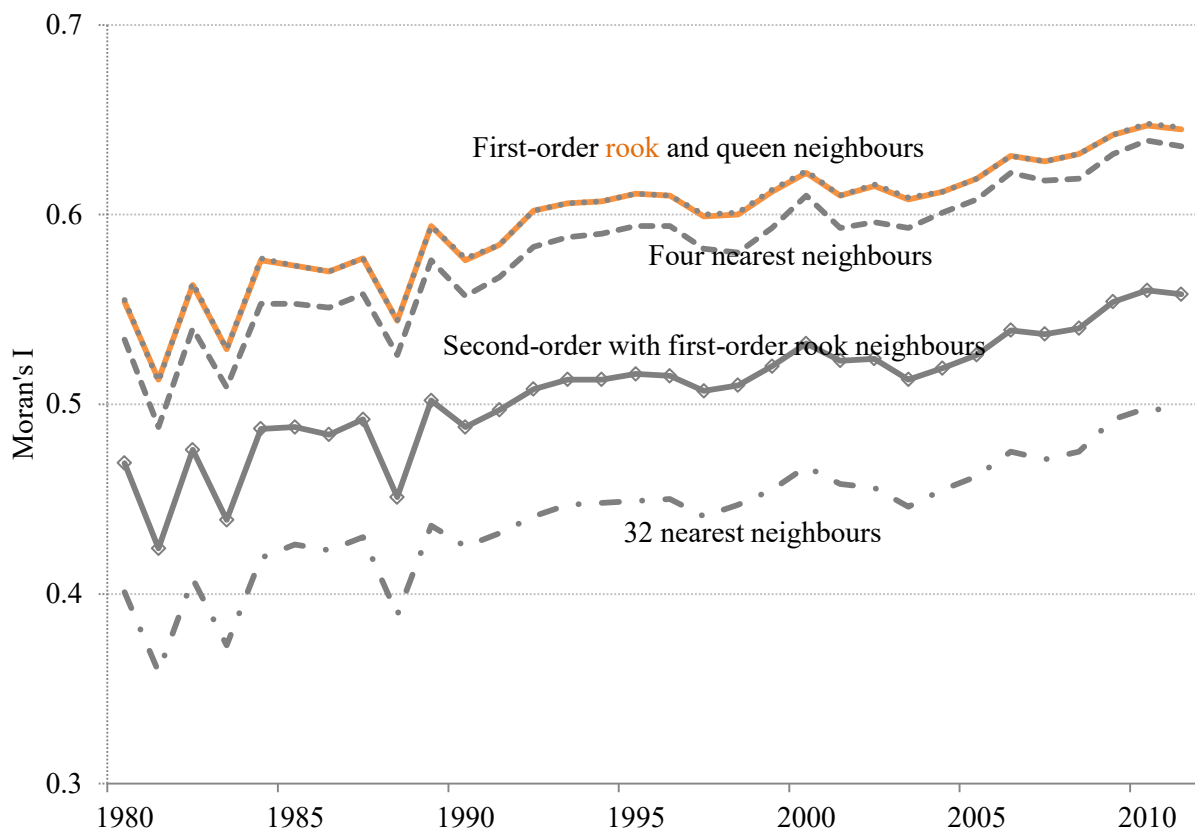


e. LISA maps of harvested area for potato.

A II-3. Generalized entropy index and the harvested area changes from 1980 to 2011.



A II-4. Moran's I of cropland with different neighbourhood matrices.



Chapter III. Determinants of changes of cropland and major crops

(Co-authors: Zhanli Sun, Liangzhi You, Daniel Müller)

Determinants of changes in harvested area and yields of major crops in China

Abstract

Global agricultural production has risen substantially in recent decades, and production must increase further to satisfy the expected future increases in demand for agricultural commodities. Production increases can be attained by expanding the cultivated area or by obtaining higher yields. Therefore, understanding the determinants of past production increases due to expansion and intensification is important. In China, the overall extent of harvested area in crop production has remained largely stable over the last few decades; however, crop composition has changed notably, and land productivity has risen sharply, mainly due to the higher use of inputs. We analysed the changes in the harvested areas and yields of the four most widely cultivated crops in China (rice, wheat, maize, and soybean) at the county level from 1980 to 2011. During this period, the harvested area of maize increased substantially, while that of rice, wheat, and soybean decreased; additionally, the yields of rice, wheat, and maize increased steadily, but the yield of soybean decreased. We used spatial panel regressions to quantify the determinants of the observed changes in harvested areas and yields for the major cultivation region of each of the four crops. Population growth, gross domestic product (GDP) growth, and urbanization positively affected harvested areas. A higher usage of machinery and fertilizer inputs were the main contributors to the increasing yields of the three cereal crops, while the harvested area and yields of soybean decreased, particularly in response to China's accession to the WTO. Our results confirm that the increasing demand from the animal husbandry sector led to the increase in domestic production of energy-rich feed crops (e.g., maize) at the expense of soybean production, which is now predominantly sourced from imports. Better understanding the determinants driving changes in crop area and yields over large areas and long time periods benefits from the improved data availability and methods and can thus generate increasingly valuable data-driven insights for evidence-based decision making.

Keywords: Spatial panel regression; agricultural production; land use intensity; crop productivity; land use change; food security.

1. Introduction

Food security continues to be a major concern for humanity, and attaining food security is an intrinsic element of sustainable development (Godfray et al., 2010a). Future food production must increase due to population growth, higher demands for plant-based energy production, and more resource-demanding diets; however, future production increases must be achieved at lower environmental costs (Alexander et al., 2015; Garnett et al., 2013; Popp et al., 2016). A few crops play a particularly important role in food security due to our reliance on a few key staple crops (Khoury et al., 2014). Overall, humanity obtains 50% of its daily calories from cereals, and more than 40% of these calories are from only three major staple crops: rice, wheat, and maize (FAO, 2019; Kearney, 2010). Moreover, the growing consumption of livestock products, which are increasingly produced in industrial production systems, requires large amounts of feed and fodder, which are mainly sourced from maize, as the source of energy, and soybean, which provides the proteins for rapid growth (Cassidy et al., 2013). Understanding changes in the area dedicated to these major crops and the changes in these areas provides critical insights for better understanding the agricultural dynamics that shape the salient changes in the food system.

In 2017, half of the 1.42 billion hectares (ha) of global harvested area was cultivated with only four crops: wheat, maize, rice, and soybean (FAO, 2019). While the overall share of the global harvested area and the share of the global production volume of these four major crops have remained stable over the last 50 years, the contribution of the individual crops to the overall production quantities has substantially changed over time. The proportion of wheat in the total harvested area decreased from 22% in 1967 to 15% in 2017. At the same time, the area occupied by corn increased from 11% in 1967 to 14% in 2017, equivalent to an absolute increase of 85 million ha (Mha). The increase in soybean cultivation has been especially drastic, with an increase greater than 95 Mha, or from 3% to 9% of the global harvested area, which is a threefold increase during this 50-year period (FAO, 2019).

The sweeping changes in the global patterns of crop cultivation have been fostered by the globalization of the global food system, manifested by the shift from locally produced food to an increasing reliance on agricultural commodities that are sourced from distant markets (Levers and Müller, 2019). However, bulky commodities, such as maize, and key staple crops, such as cereals, continue to be produced domestically, mainly to reduce reliance on imports and to guarantee domestic food security (Huang et al., 2017). Where these crops are produced depends on locational factors that shape land rents, including climate, soil, and accessibility, while changes in economic, institutional, political, and demographic

characteristics drive changes in cultivation patterns (Meyfroidt, 2016). Empirically quantifying how changes in the demand for domestic crop production affect the land use extent and where land use intensity will increase in response to rising demands remains necessary.

Much of the recent production increases have been due to the higher crop yields, mainly as a result of higher input intensity per unit area (Magliocca et al., 2014; Rudel et al., 2009). This intensification involves a higher use of intermediate inputs, such as fertilizers, pesticides, water, labour, and capital per unit area (Erb et al., 2013; Xu and Chi, 2019). The intensification of production has greatly benefitted global food security because it has saved substantial land resources from being converted into agricultural production (Borlaug, 2007; Burney et al., 2010). However, intensification may also be associated with rebound effects by raising profits from production and lowering food prices, thereby incentivising further expansion (Lambin and Meyfroidt, 2011; Rudel et al., 2009). Understanding the patterns and determinants of intensification processes remains important because of the adverse side effects of higher input intensity, such as nutrient leaching, water pollution, air pollution, and negative effects on human health (Godfray et al., 2010b; Tilman et al., 2011).

China is an interesting case because the country's rapid economic development has had substantial effects on land use (Deng et al., 2015; Jiang et al., 2013; Sun et al., 2018). Agricultural production has increased dramatically in China since the reforms that started in 1978 and since resource use rights shifted to farm households. Since the 2000s, many rural areas have started to depopulate and are suffering from labour shortages because of the increasing migration rates to growing cities (Liu et al., 2017). Maintaining domestic food security, defined by the Chinese government as a 95% degree of grain self-sufficiency, remains a top policy priority and is a strategic goal on China's food security agenda (Huang and Yang, 2017).

At present, China is by far the largest producer and consumer of rice and wheat in the world; the government views self-sufficiency in the production of these crops as critical for securing China's "rice bowl" (i.e., producing sufficient food for China) (Zhang, 2019). To achieve the policy goals, the Chinese government has implemented a strict policy to protect its arable land, the so-called "arable land red line policy", that aims to maintain at least 1.8 billion mu (i.e., 120 Mha) of agricultural land in production. In addition, China set up a guaranteed grain procurement price for wheat, rice and maize, among others, to foster grain

production. Hence, monitoring changes in the extent and structure of agricultural land continues to be important in setting China's agricultural policy agenda.

China faces daunting challenges in striving for the envisaged domestic food security. The domestic demand for agricultural products has been rapidly increasing, mainly because of population growth; additionally, growing affluence and urbanization shifted Chinese diets away from mainly plant-based food towards diets with a higher reliance on livestock products (Huang et al., 2015; Jiang et al., 2015). However, the very small farm structure (the average farm size in China was approximately 0.5 ha in 2015 (Wu et al., 2018)) and the high fragmentation of farms hinder the higher input of capital, agricultural modernization, and realization of economies of scale (Zhang et al., 2013). As a result, the total grain production has stagnated in recent years after the 12 years of production growth since 2003 (Zhang, 2019). The scarcity of land resources in China becomes even more severe with the loss of arable land caused by urbanization, land degradation, and soil contamination (Bren d'Amour et al., 2016a; Deng and Li, 2016). The contrast between the low income from agriculture and the rising wage levels from urban employment opportunities nourishes the massive migration from rural to urban areas. The ageing society, partially due to the one-child policy, further augments rural labour scarcity and raises the question of who will cultivate China's agricultural land in the future. These fundamental changes in the Chinese countryside have deep effects on the extent and input intensity of agriculture and thus on production outcomes. It is urgent to understand the impact of these changes on agricultural production strategies and thus on agricultural productivity.

The composition of crop cultivation has changed notably in the last three decades. Rice, as the most important staple food for the Chinese, has traditionally been cultivated in southern China. However, in recent years, rice cultivation has expanded towards Northeast China because the japonica rice preferably grown in the north is in high demand due to its superior nutritional value and good taste (Sun et al., 2018). In contrast, the harvested area of rice farther south has decreased due to cropland abandonment (Liu et al., 2013). Combined with climatic change, the centre of the rice plantation area has already shifted 230 km to the northeast (Hu et al., 2019; Li et al., 2015; Liu et al., 2013). Wheat is the main staple crop in northern China. Approximately 126 million metric tons of wheat was produced on 24 Mha in 2011, and most of this wheat was cultivated extensively and rotated with maize. Moreover, China has become the second largest maize producer in the world. The harvested area of maize increased from 20 Mha in 1980 to 36 Mha in 2011, mainly in

response to rising prices, as maize is the major feed crop for China's growing livestock population. Maize production is concentrated in the plain regions from the northeast to southwest (Li, 2009; Yin et al., 2018). Overall, rice, wheat, and maize account for 80% of the total harvested area in China, with an increasing trend. However, the area cultivated with soybeans decreased slightly, and yields have remained stable since approximately 1980 (Sun et al., 2018).

The stark implications of the changes in harvested area, crop structures, and yields on food security in China require a better understanding of the determinants of these changes. However, the existing literature on the patterns, determinants, and drivers of cropland structures in China has focused on individual crops, such as rice (Hu et al., 2019; Li et al., 2015; You, 2012) or maize (Li, 2009). To the best of our knowledge, a holistic assessment of the spatial changes in cropping structures and productivity, how these properties have changed in all of China, and what factors have determined these changes is lacking. Here, we analyse the determinants driving the changes in harvested areas and yields of four major crops (rice, wheat, maize, and soybean). To do so, we use spatial panel regressions that account for both spatial autocorrelations in the data and serial correlations. We aim to answer two key research questions:

1. How did the harvested areas and yields of the four major crops change between 1980 and 2011?
2. What were the main determinants driving the changes in the harvested area and yield of each of these crops?

2. Data

We utilize spatial panel data from 2,354 counties and from each year from 1980 to 2011. All data are sourced from the statistical yearbooks of the Chinese government (Chinese Statistics Yearbook, 1980-2011). The panel data setup allows us to control for variables that cannot be observed or measured, such as cultural factors or differences in agricultural practices across observations, and to control for variables that change over time but not across observations (Hsiao, 2007).

We focus our analysis on the four major crops, i.e., rice, wheat, maize, and soybean, and specifically assess their harvested areas. In 2011, these crops covered 90% of the cultivated areas in China and 92% of the grain production quantity. The annual harvested areas of

each of the four crops in ha and yield in tons per ha served as the dependent variables in the crop-specific regressions.

Overall, the total harvested area of the four crops increased by 6%, from 90 Mha in 1980 to 95.7 Mha in 2011. Between 1980 and 1998, the harvested area increased by approximately 5%, interrupted by a decline from 1998 to 2003, and it recovered again between 2004 and 2011. Maize showed the largest increase of 74%, while rice and wheat decreased by 14% and 10%, respectively. Soybean accounted for 8% of the total harvested area and only marginally increased by 0.1% from 1980 to 2011.

Crop production in China is spatially clustered in specific regions (Sheng et al., 2017; Yin et al., 2018). For our crop-specific regressions, we confine the data for each regression to the main cultivation region of each of the four crops. To define these regions, we selected the provinces with the largest harvested area in descending order until more than 90% of the entire harvested area of each crop was included. The main cultivation region visualizes the most important centres of production for each crop in 2011 (Figure III-1). Rice is clustered in Northeast and South China, wheat is mostly located in the northern part, and maize dominates a belt from the northeast to southwest. Soybean is concentrated in the northeast. In contrast to the harvested areas of each of the four crops, the crop yields did not show obvious spatial clusters (A III-1).

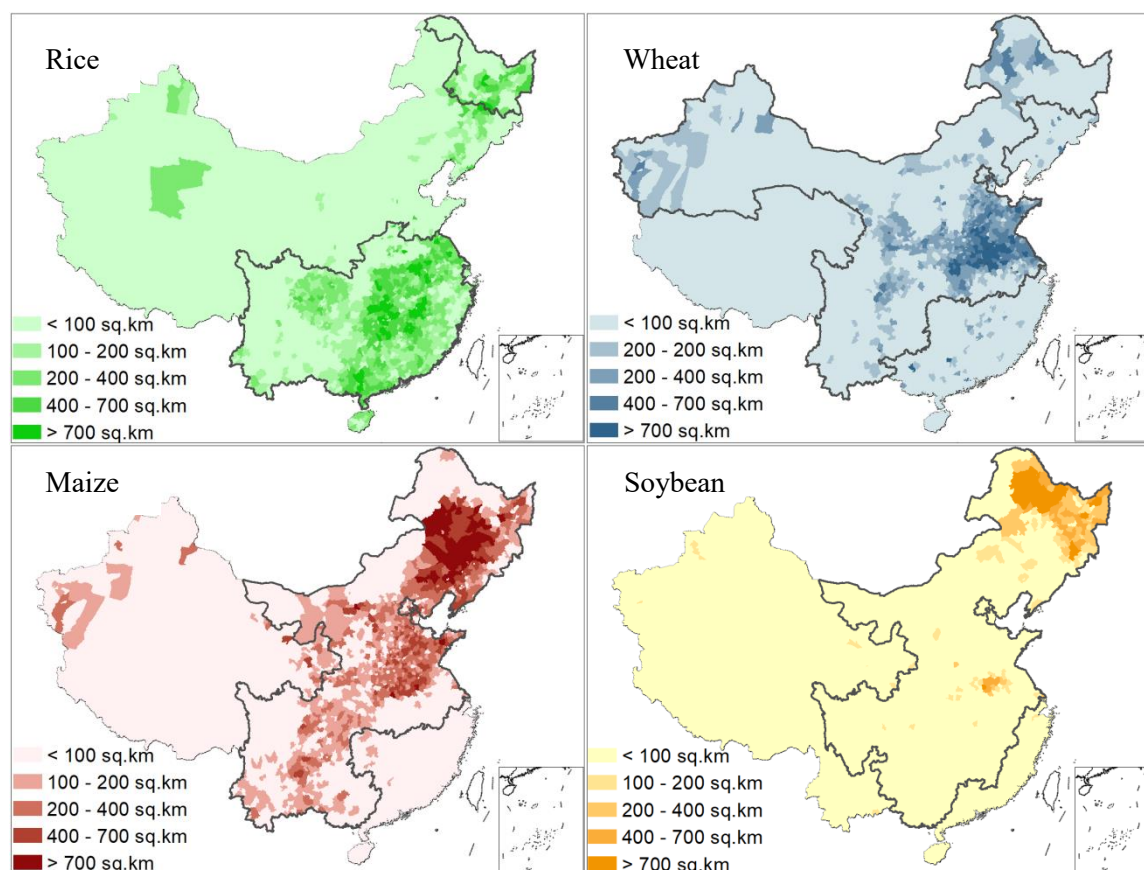


Figure III-1. Main cultivation region of each crop (thick black outline) with the harvested area values in 2011.

We also selected all explanatory variables from the statistical yearbooks of China. The choice of the variables was based on a thorough literature review and prior knowledge about land use in China (Shi et al., 2013; Tong et al., 2003; Yu et al., 2016). As socioeconomic variables, we include gross domestic product (GDP) per county as a proxy for economic performance. Road length per county is used as a proxy for market accessibility. The population per county measures the local demand for agricultural products, which may affect the extent and patterns of cultivation. We account for the agricultural labour input, the horsepower of machinery used in agricultural production, and the use of fertilizer in agricultural production to represent land use intensity. We further employed two time-variant biophysical factors that we hypothesized to be important spatial determinants for the location of crop cultivation: the accumulated temperature over 10 degrees and the total rainfall per year. The included time-invariant geographic factors are elevation, distance to the nearest provincial capital, and soil condition. Finally, we include a dummy variable that captures the admission of China to the World Trade Organization (WTO) in 2001 as a potentially important variable affecting the amount of crop imports and the domestic patterns of agricultural production.

All variables are available at the county level and at an annual resolution from 1980 to 2011. While the application of capital inputs for agriculture (machinery, fertilizer), as well as GDP and road length have increased substantially for all crops, labour input has decreased (Figure III-2). The population increased by approximately 35% over the study period, and the growth was fastest in the rice region; in contrast, agricultural labour decreased by approximately 20%, with the highest absolute decrease in the rice region, suggesting that this region has rapidly urbanized. As expected, rainfall and growing degree days fluctuated over time, with a slight increasing trend in the number of growing degree days.

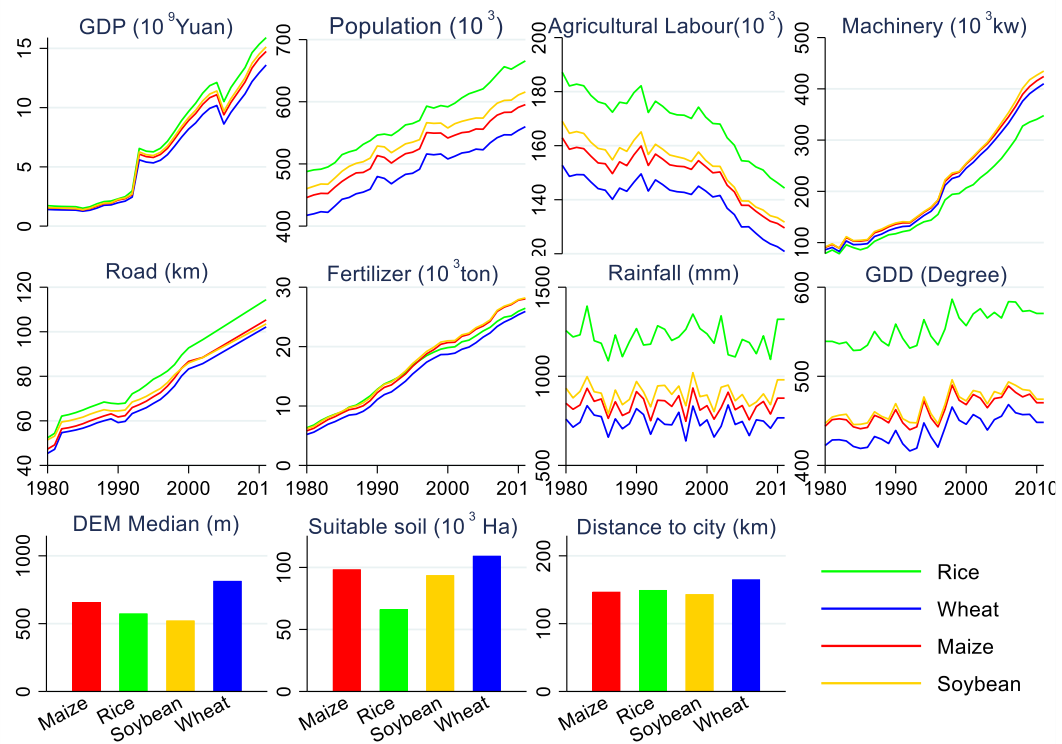


Figure III-2. Trends of explanatory variables within the main cultivation regions of rice, wheat, maize, and soybean.

3. Methodology

The harvested areas and yields are spatially autocorrelated in China (Yin et al., 2018). The regression models must correct for spatial autocorrelations because it violates the standard assumption of independent observations in regression analysis, similar to serial correlations in time series data. We correct for the autocorrelations over time and space with spatial panel models (Belotti and Hughes, 2017; Elhorst, 2012, 2010). Spatial panel models capture interactions across spatial units and over time. These models fall into two broad

categories, depending on whether the spatial interdependence follows a pattern of spatial autocorrelation, i.e., similar values cluster in the surroundings, and hence, the values may depend on each other. The second category is spatial heterogeneity, which can be due to systematic changes in the relationships over space (Anselin et al., 2008, 2006).

To test for the presence of spatial autocorrelation in the dependent variables, we calculated Moran's I separately for harvested area and yield for all cultivation regions of the four crops. We consistently found statistically significant spatial clustering, implying the existence of positive autocorrelation. We controlled for the spatial autocorrelation by selecting between different models that controlled for time lags, spatial lags, spatial errors, or a combination thereof. To select the appropriate model, we used the Akaike information criteria (AIC) and the Bayesian information criteria (BIC), which suggested the dynamic spatial autoregressive model. Finally, we used the Hausman test to decide between random and fixed effect formulations, and the results suggested the fixed effects formulation was appropriate. Consequently, all time-invariant variables cancel out of the regressions. The dynamic spatial lag model is as follows:

$$y_t = \tau y_{t-1} + \rho W y_t + \beta X + \varepsilon \quad (\text{Equation 1})$$

τ captures the influence of the values of the dependent variables in the earlier time step ($t-1$) on the outcome y at time t . W is an $n \times n$ spatial weights matrix that describes the spatial arrangement of the observations, and w_{ij} is the (i, j) th element of W , where i and $j = (1, \dots, N)$. ρ is the spatial autoregressive coefficient, and ε is the error term. τy_{t-1} denotes the value of y in the previous year, and $\rho W y_t$ is the spatially weighted average of the value of y in the neighbouring locations or the spatial lag term. X is the vector of the explanatory variables.

The spatial weights matrix, w , accounts for the spatial autocorrelation. Unfortunately, there are no universal rules selecting the neighbourhood size, structure, and weight of individual neighbours. We therefore tested several realizations of the spatial weights matrix to assess the sensitivity of the results to the particular choice of the neighbourhood structure. Here, we report the results with the first order of rook contiguity weights, which include immediate neighbours that share a common border with the observation of interest. The implementations of the other weight matrices have minor effects on the results and do not affect their interpretation; these results can be obtained from the authors upon request. Finally, we verify the correlation between variables with the variance inflation factor (VIF). As a rule of thumb, a variable with a VIF value greater than 10 may merit further

investigation (Miles, 2014). No major correlative structures of concern occurred in our data, as judged by the VIFs.

We present all regression results in log-log form so that we can interpret the variable effects as elasticities, expressed as a percent change. For example, a coefficient of two signals that a 1% increase in the independent variable would result in a 2% increase in the dependent variables. In addition to comparing the size of the influence of each coefficient for all crops, we also calculate the standardized effect sizes that facilitate comparing the strengths of influence across the explanatory variables, irrespective of their measurement units.

4. Results

4.1 Changes in harvested area and yield

Here, we present the changes in the main cultivation regions; hence, the reported changes may differ slightly from the official numbers reported in national statistics. The average harvested area of maize increased, while that of rice and wheat decreased. The areas of maize and soybean increased by 78% and 7%, respectively, while the areas of rice and wheat declined by 14% and 9%, respectively, especially between 1998 and 2004 (Figure III-3). The yields of rice, wheat, and maize increased by 40%, 46%, and 61%, respectively. The yield of soybean, however, decreased by 33% from 1980 to 2011 (we surmise that the spike in the maize and wheat yields in 1983 is a data artefact; this outlier will not substantially affect the results because we have a long time series).

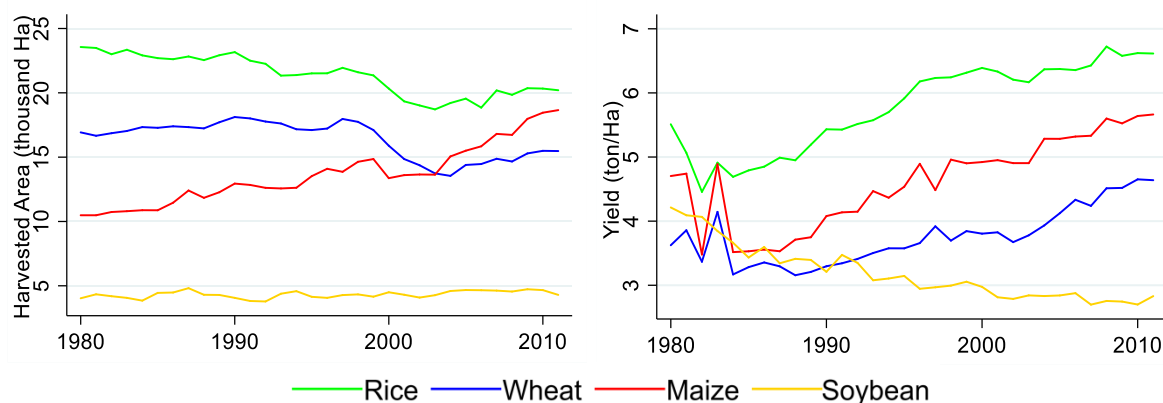


Figure III-3. Changes in harvested areas and yields in the main cultivation regions.

Between 1980 and 1990, rice increased in the northeast and rice declined in southern China, mainly from 1990 to 2000 (maps with the spatial changes in harvested areas from

1980 to 2011 are shown in Appendix A III-2, and yield changes are shown in Appendix A III-3). Between 2000 and 2010, the harvested areas mainly decreased close to the coast in south-eastern China but slightly increased in the northeast and south. Rice tended to increase in the northeast and decrease in the south along the coastline, possibly because of urbanization. The main areas of wheat cultivation were in northern China, although some wheat was found in almost every province. The spatial patterns of changes in wheat cultivation from 1980 to 2011 were not as clear as those for the other crops; however, the spatial clustering around the North China Plain, the traditional wheat cultivation region, seemed to have strengthened. Maize cultivation covered large areas stretching from the northeast to southwest; this area is known as the Chinese maize belt (Meng et al., 2016). Soybean was increasingly concentrated in the northeast.

Crop yields showed a much more heterogeneous distribution than area harvested. The yields of rice, wheat, and maize increased in most regions in China, while the yield of soybean decreased, especially between 1980 and 1990.

4.2 Determinants of the changes

The first-order time lag and spatial lag of the dependent variables have strong and positive effects, which suggest strong time trends and mirror the spatial concentration of the harvested areas of each crop (see A III-4 for detailed regression results).

The impacts of time-varying explanatory variables quantify the effects in percent changes (Figure III-4 visualizes the estimation of changes in harvested areas, and Figure III-5 shows the results of changes in yields). Population positively affects the harvested area of crops; a 1% increase in population is associated with a 0.1% increase in harvested area for all four crops. Rising agricultural labour per county also has a consistent positive influence on every crop, and it is strongest for soybean, at 0.1%. Increasing road length tends to be associated with less harvested area of rice and soybean, but wheat and maize tend to benefit from a denser road network. GDP, agricultural machinery, WTO accession, and rainfall have negligible influences on harvested area.

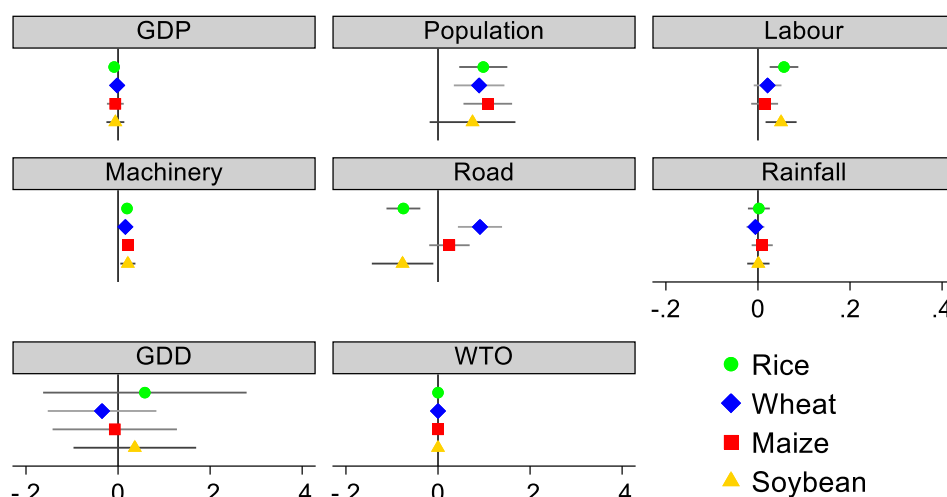


Figure III-4. Percentage change in harvested areas of each crop with a 1% increase in the explanatory variables; markers are coefficient estimates, and whiskers denote the 95% standard errors.

In terms of yield changes, a 1% growth in GDP positively influenced the yields of rice (0.02%), wheat (0.01%) and maize (0.03%) but was negatively associated with the soybean yield (-0.02%) (Figure III-5). The rising population had little influence on yields, while more production inputs, including labour, machinery, and fertilizer, were consistently important. The increase in road length was positively correlated with the yield growth of rice and soybean. Weather conditions were, unsurprisingly, important determinants for yields. A 1% increase in growing degree days was associated with a 0.1% increase in yields. Higher rainfall contributed to lower yields of rice and soybean, while it was associated with higher yields of wheat and maize. The WTO accession in 2001 was associated with an increase in wheat and maize yields, while it had a negative effect on rice and soybean yields.

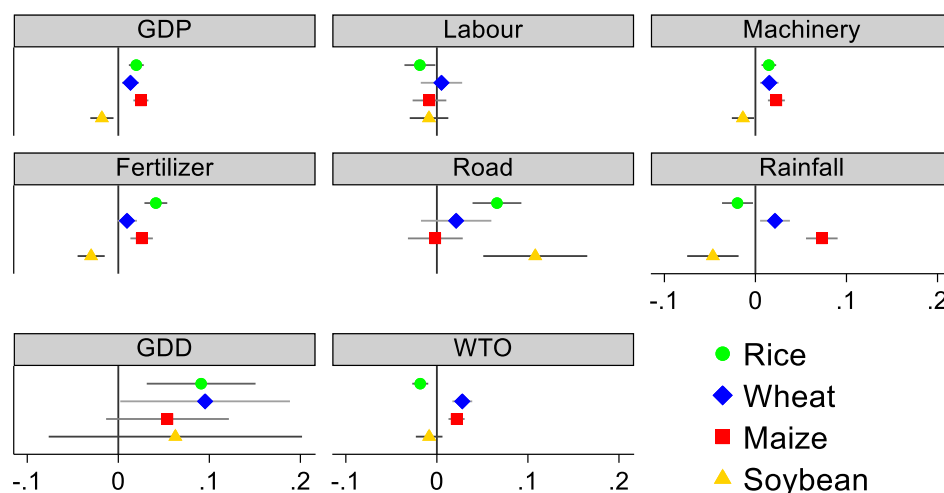


Figure III-5. Percentage change in yields of each crop with a 1% increase in the explanatory variables; markers are coefficient estimates, and whiskers denote the 95% standard errors.

The comparison of the variables with the standardized regression coefficients reveals the relative influence of each covariate in the crop-specific regression (Figure III-6; see A III-5 for the detailed regression results). A higher population is the most important determinant of all four crops, with more people being associated with more harvested area. In addition, the harvested area of rice is mostly positively affected by more agricultural labour and machinery and negatively influenced by more roads and a higher GDP. Wheat area is negatively related to higher growing degree days and GDP. The maize area is mainly shaped by machinery and rainfall. The harvested area of soybean is negatively associated with greater road length. Interestingly, accession to the WTO contributed to a decrease in the harvested area of soybean.

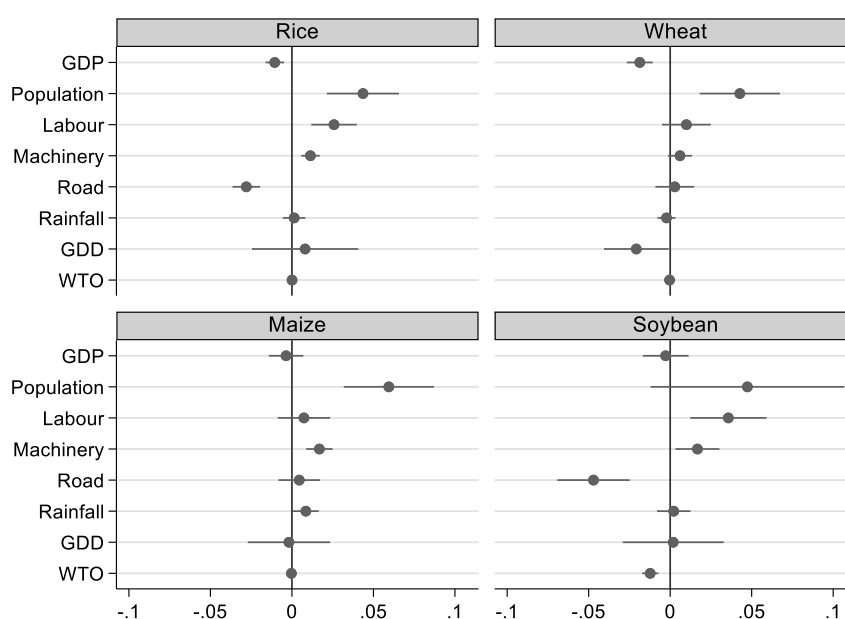


Figure III-6. Variable importance for changes in harvested areas of each crop; dots are standardized coefficients, and whiskers denote the 95% standard errors.

In terms of yield, higher fertilizer input is the most important explanatory factor for higher yields of rice, wheat, and maize, while fertilizer has a negative effect on soybean yields, as soybeans are a nitrogen-fixing crop that requires low fertilizer inputs (Figure III-7). Machinery inputs have a substantial positive impact on crop yields, except for soybean, while higher labour inputs tend to be associated with lower yields. Road construction is the most important determinant for higher soybean yield. Again, as expected, the weather variables are important for yields of all crops, albeit with varying degrees of influence.

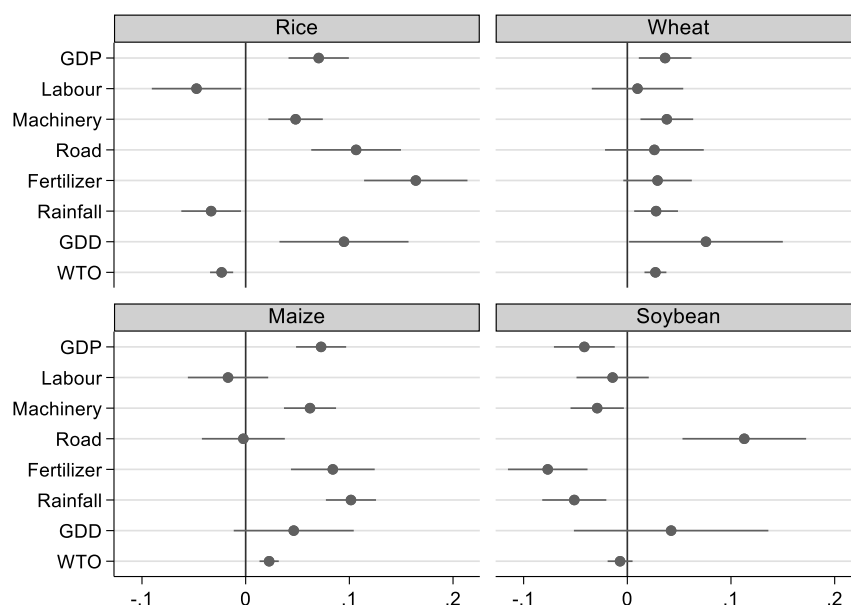


Figure III-7. Variable importance for changes in yields of each crop; dots are standardized coefficients, and whiskers denote the 95% standard errors.

5. Discussion

The yields and the harvested areas of crops are the two main factors determining total crop production. In this study, we evaluated the changes in both areas and yields for rice, wheat, maize, and soybean in the major producing regions of these respective crops in China using county-level data from 1980 to 2011. We use spatial panel regression to quantify the determinants of the observed changes.

We show that cropping structures have changed substantially over recent decades, with maize occupying more area, mainly at the expense of wheat and rice. Maize has been particularly important in terms of providing energy-rich feed to Chinese grown livestock. In particular, the increasingly dominant industrial production of pigs and poultry relies on domestic maize production to provide energy for rapid animal growth (Bai et al., 2018). At the same time, protein feed, which is another important ingredient for the growing livestock sector, comes from soybean. However, China has increased its imports of soybean from abroad, which was also spurred by its accession to the WTO in 2001; however, the area of domestic soybean cultivation has slightly contracted, and the yields have declined. The large amount of imported soybeans meets the demand of the rapid increase in protein feed in China, while it allows China to save scarce arable land for main grain crops (Qiang et al., 2013). At the same time, the growing soybean imports of China have contributed to land use change elsewhere, such as in Latin America, where most of the soybeans imported by China are produced (Porkka et al., 2013; Yu et al., 2016). This is

worrying for China's nitrogen balance because soybean, a legume, fixes nitrogen from air and soil in its biomass. Thus, the contraction of soybean production also necessitates much higher nitrogen inputs to N-demanding crops, such as maize (Sun et al., 2018).

China has dramatically increased grain production in recent decades (You et al., 2011), mainly due to the increased yields of rice, wheat, and maize production, while the harvested areas of rice and wheat have declined by 14% and 10%, respectively. Yield levels are mainly the result of management as well as the application of intermediate inputs, such as pesticides and fertilizers. Our analysis corroborates the importance of input levels on yield increases. While lower labour intensity has dampened crop yields, the decrease in labour was more than compensated by the higher fertilizer use and machinery applications for the three cereal crops. Labour input will decrease further as more people migrate from rural areas to cities, resulting in increasing labour shortages in agricultural activities (Huang and Rozelle, 1996; Liu et al., 2016).

Most rice fields are located in South China, with regions that have been characterized by high rates of economic development and rapid urbanization. Because rice cultivation in this region demands considerable labour input due to the extremely fragmented land plots and hilly terrain and provides comparatively little income, off-farm jobs in cities and other sectors continuously pull labour out of agricultural production (Peng et al., 2009). As a result, agricultural income has a decrease proportion in the total income of rural households in this region. As a consequence, the GDP growth and rural-urban migration in these regions has led to a decline in the harvested areas of rice, particularly in coastal regions. In addition, due to the increasing demand for high-quality rice produced in north-eastern China and the warming climate, rice has expanded substantially in the north in recent years (Li et al., 2015; You, 2012). Our analysis and results on the effects of GDP and growing degree days confirm this narrative and are in line with findings from other scholars (Deng et al., 2015; Gornall et al., 2010; Wang et al., 2018).

Population growth is often associated with the expansion of harvested area because population growth increases the pressure on local land. In China, population growth has combined with rapid urbanization and rising income levels to substantially increase the food demand. In particular, the shift to higher meat consumption resulting from rising affluence, particularly by urban consumers, has contributed to substantial land conversion to feed crops (Godfray et al., 2018), such as maize. Meanwhile, the growing imports of other crops, such as soybean, lessened pressure on the land (Sun et al., 2019). The

development of the road network, better transportation infrastructure, and accession to the WTO has facilitated food imports rising. However, there is ample evidence that a further increase in the application of intermediate inputs will not elevate crop yields much more, as the input applications are already very high in many areas of China, leading to levels of air and water pollution that are of concern (Wang et al., 2018).

One limitation of this research is that the agricultural input values are lumped together at the county level; however, crop-specific values are not available. As all counties grow more than one crop, we cannot associate the amounts of fertilizer, machinery, and labour that are applied to each of these crops, and we cannot relate the changes in input applications to the changes in crop-specific production patterns. This uncertainty causes some inaccuracies and insensitivities in the input variables, as shown by our results. For example, soybean was not the dominant crop in most regions except in some counties in north-eastern China; thus, the fertilizer, machinery, and labour values at the county level may not adequately reflect the input intensity of soybean. This pattern explains some seemingly counterintuitive results, such as that labour has little effect on soybean crop yield. In addition, the actual labour input is difficult to estimate, as labour has been increasingly shifting from the agricultural sector to the manufacturing and service sectors. The increase in the number of rural labourers may not necessarily imply a higher input of labour in crop production, which may explain the negative effects of labour on yields, as shown in the results. Nevertheless, the analysis suggests that labour is not a major constraint for further yield increases in Chinese crop production. Despite the data limitations, our national-level analysis at the relatively coarse resolution of counties spanning a period of 32 years clearly reveals some pertinent trends in crop production in China. We trust that our work can stimulate further discussion and analysis, as we believe such nationwide analysis complements many useful analyses at the level of farms that have a smaller geographic coverage. Comparisons of the analyses at the micro- and macro-levels are needed to attain a holistic picture of the agricultural production dynamics in China.

6. Conclusion

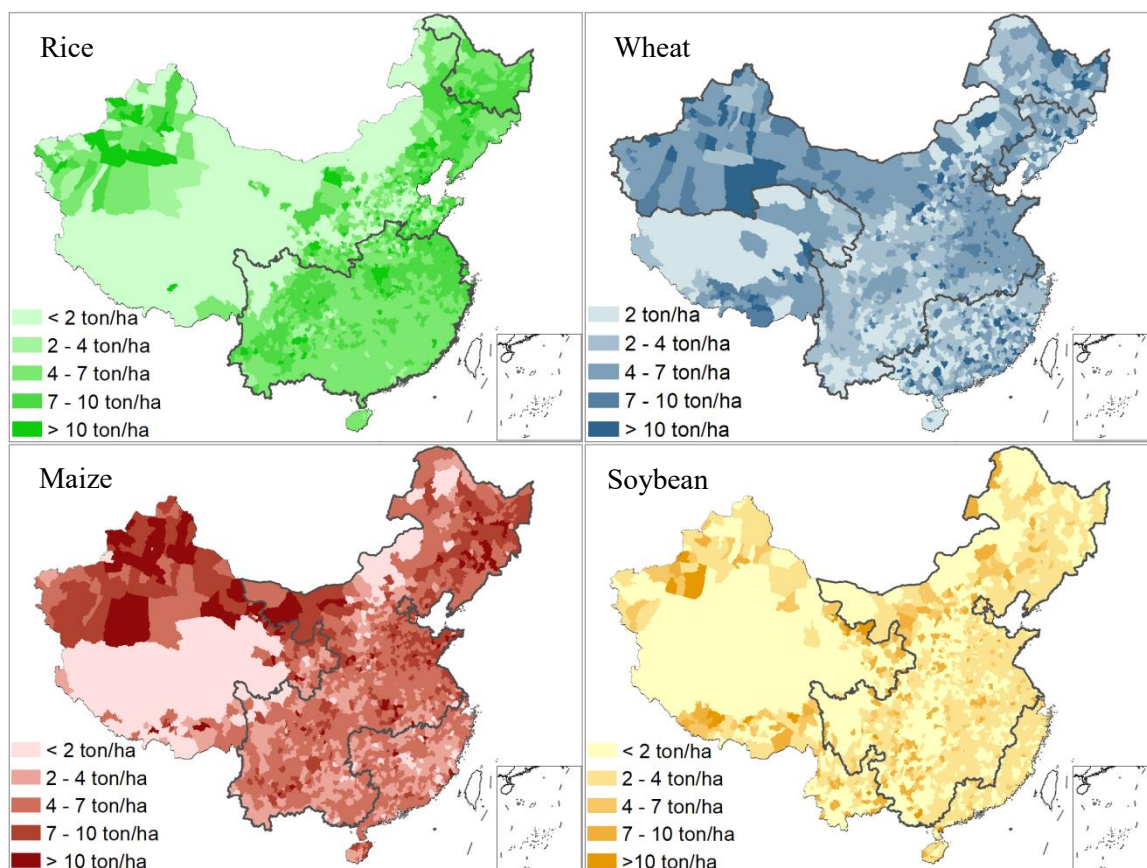
Spatial econometric analysis allows us to better understand the determinants affecting the harvested areas and yields of major crops over time and space. Here, we reveal the distinct changes in harvested area from 1980 to 2011, most notably the increase in maize and the contraction of wheat and rice. As a result of the increasing yields of grain crops, China is

almost self-sufficient in rice, wheat, and maize production despite its increasing domestic demand. However, the liberalization of trade has driven stagnation in domestic soybean cultivation, which is almost entirely imported.

Overall, our analysis demonstrates the complex interactions among intertwined determinants affecting the area and yield changes in China. Further research with statistical data of a higher spatial resolution could corroborate our conclusions and allow for more nuanced insights into the dynamics within the counties. In light of the many impacts of changes in crop production on food security and the environment, it is important to reveal the patterns and determinants of the changes across large areas. Such analysis will also benefit from longer time series and methodological improvements, such as in spatial econometrics, that allow for a deeper analysis of space-time data. The sustainable development of Chinese agriculture can benefit greatly from evidence-based decision making with data-driven insights.

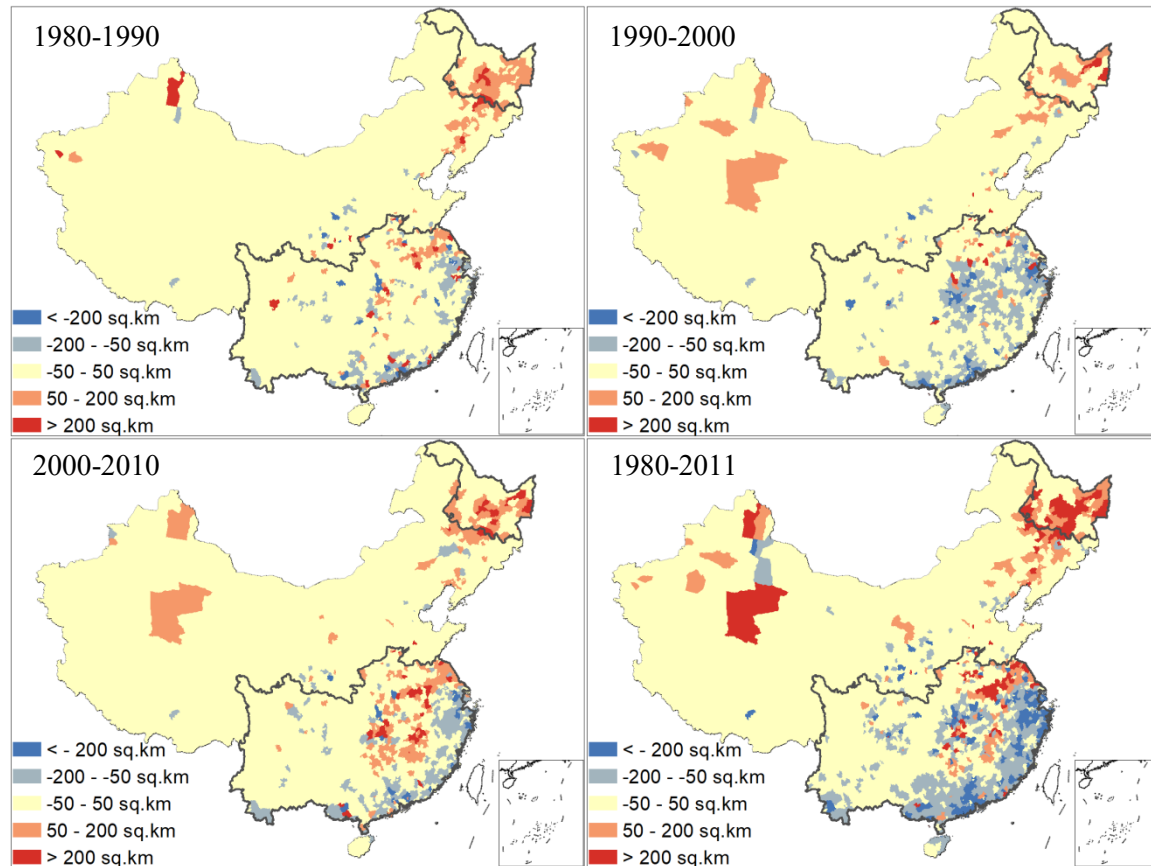
Appendix III

A III-1. Yield distribution of four crops in 2011.

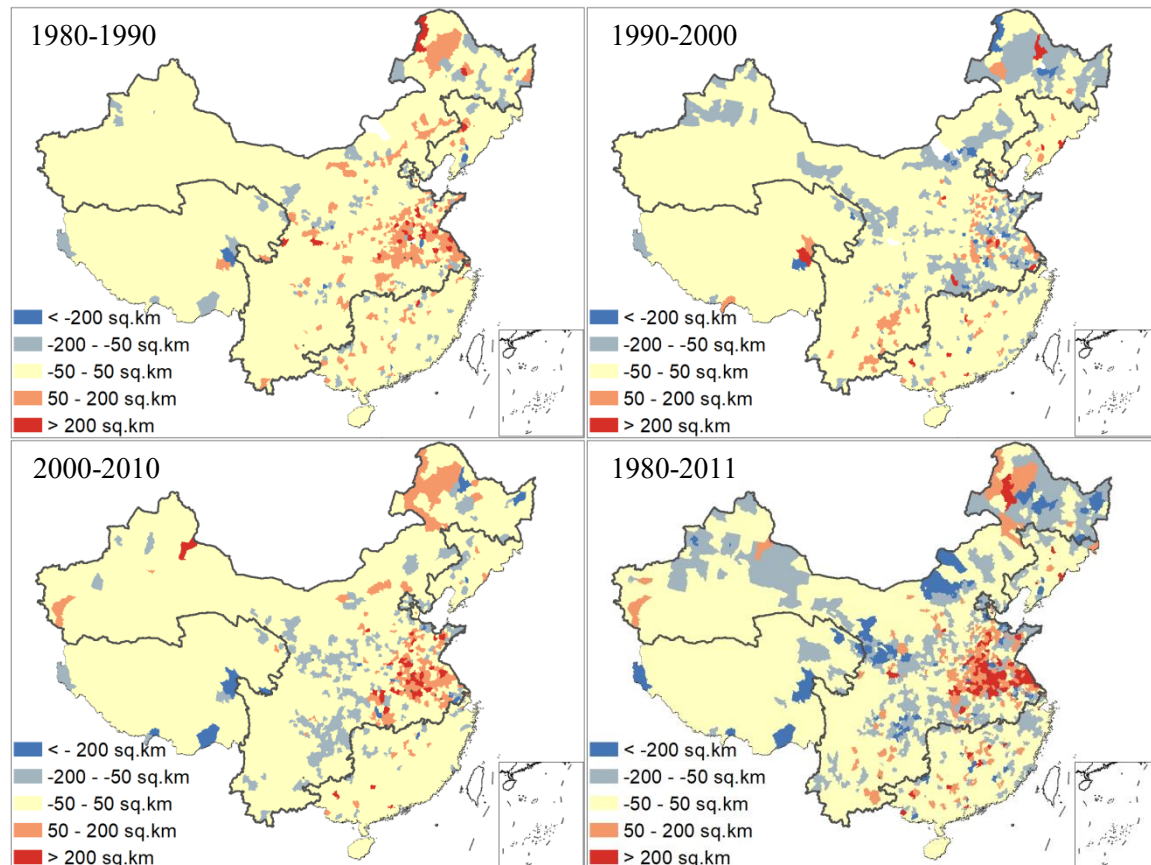


A III-2. Area changes in four major crops in 10-year intervals.

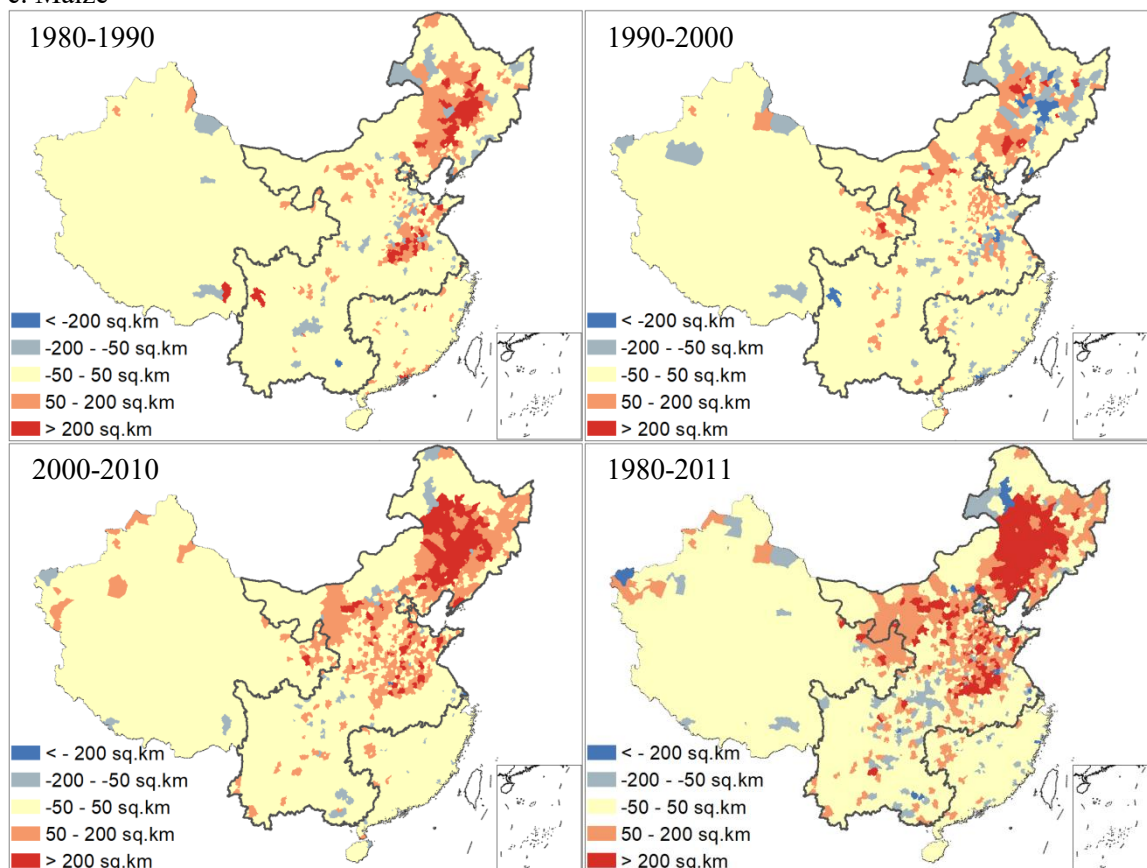
a. Rice



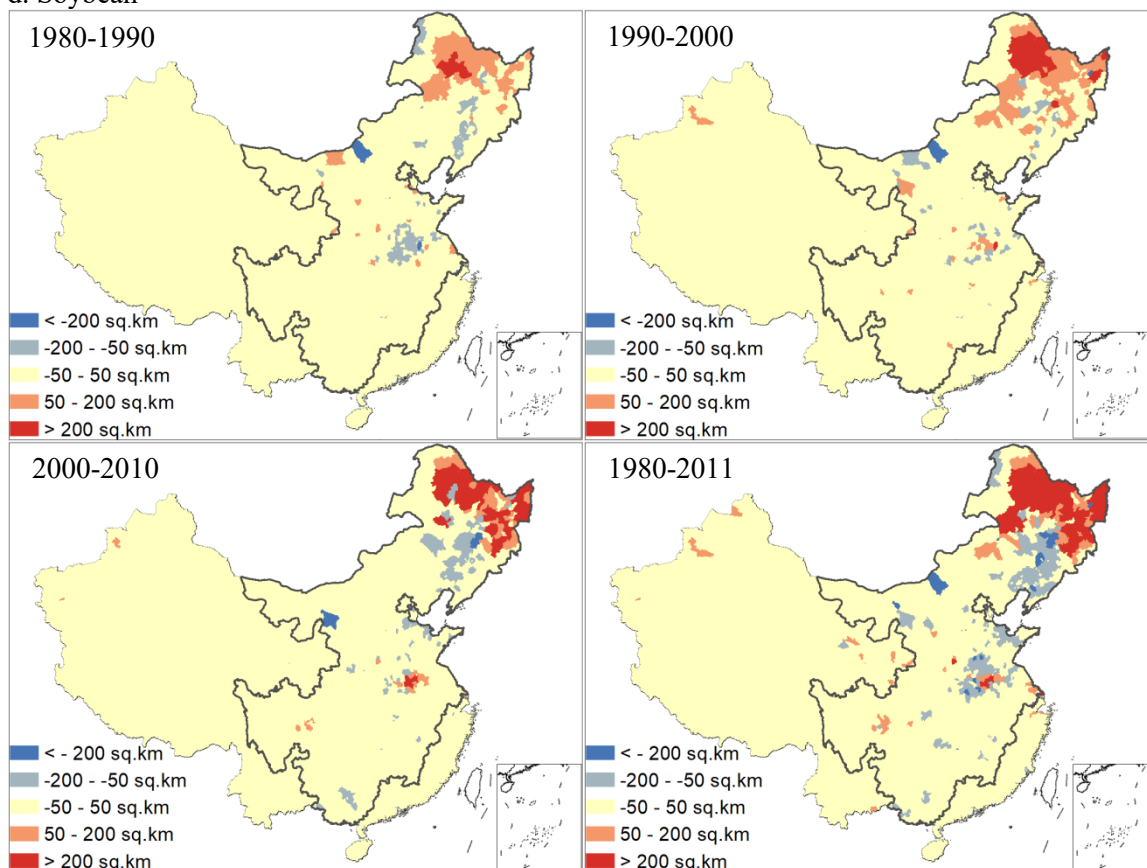
b. Wheat



c. Maize

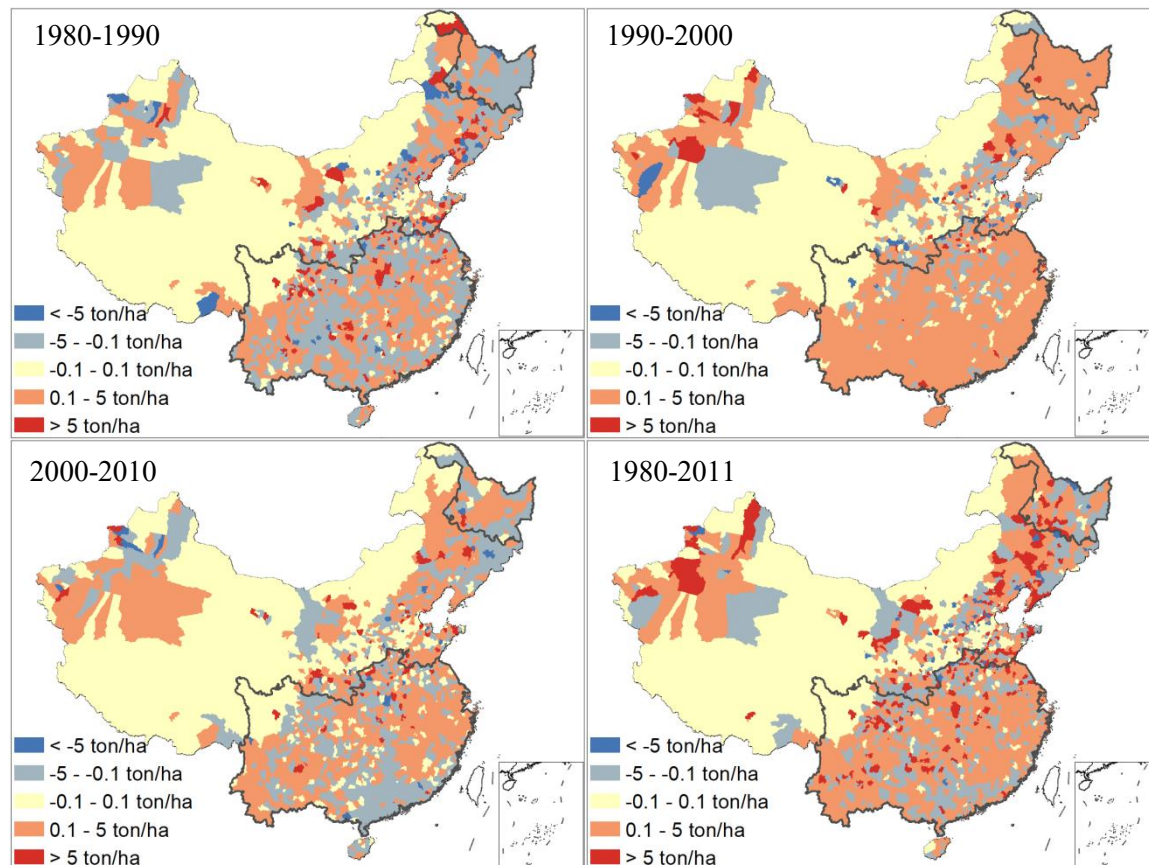


d. Soybean

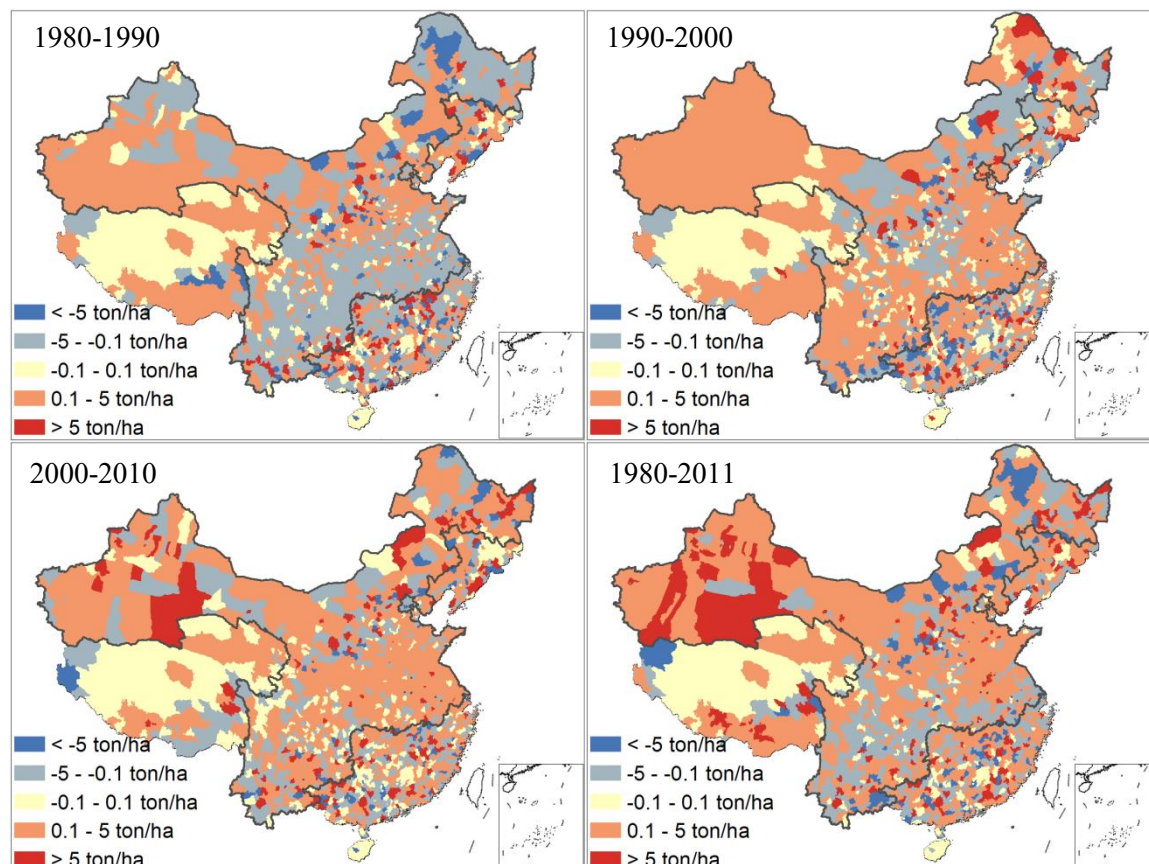


A III-3. Yield changes in four major crops in 10-year intervals.

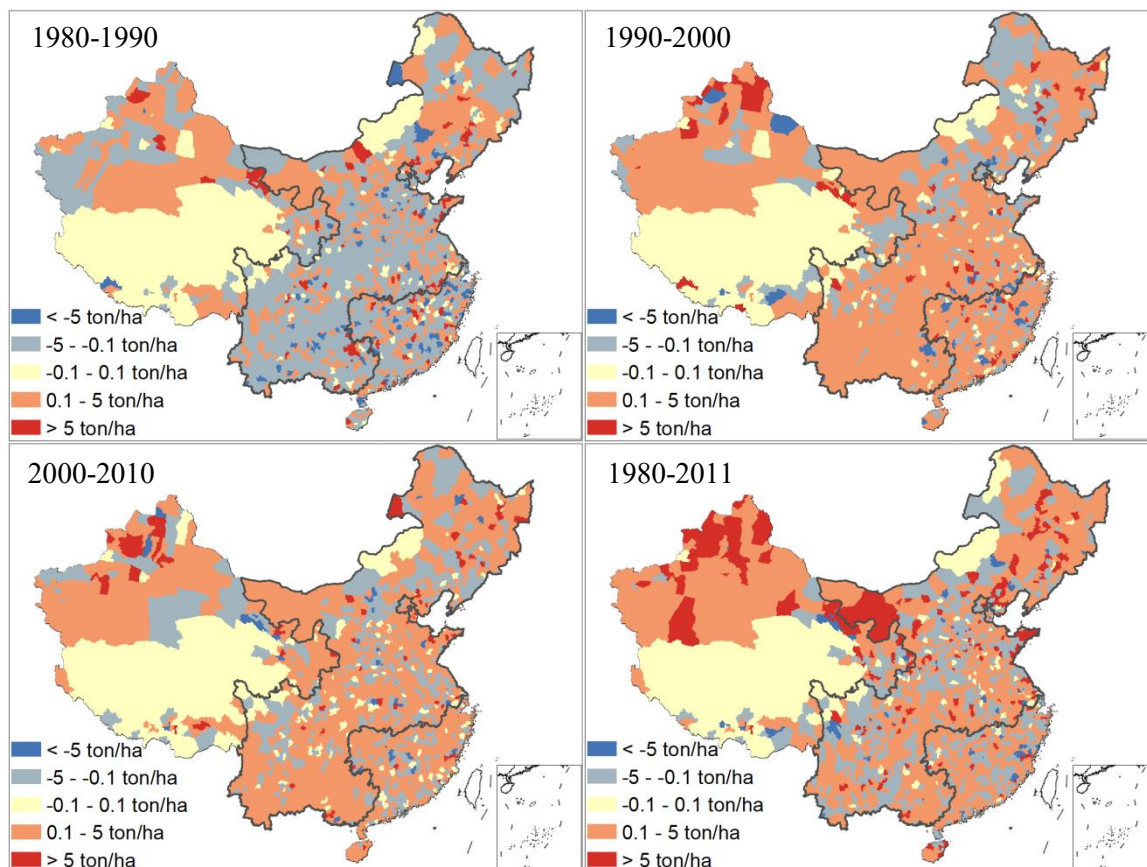
a. Rice



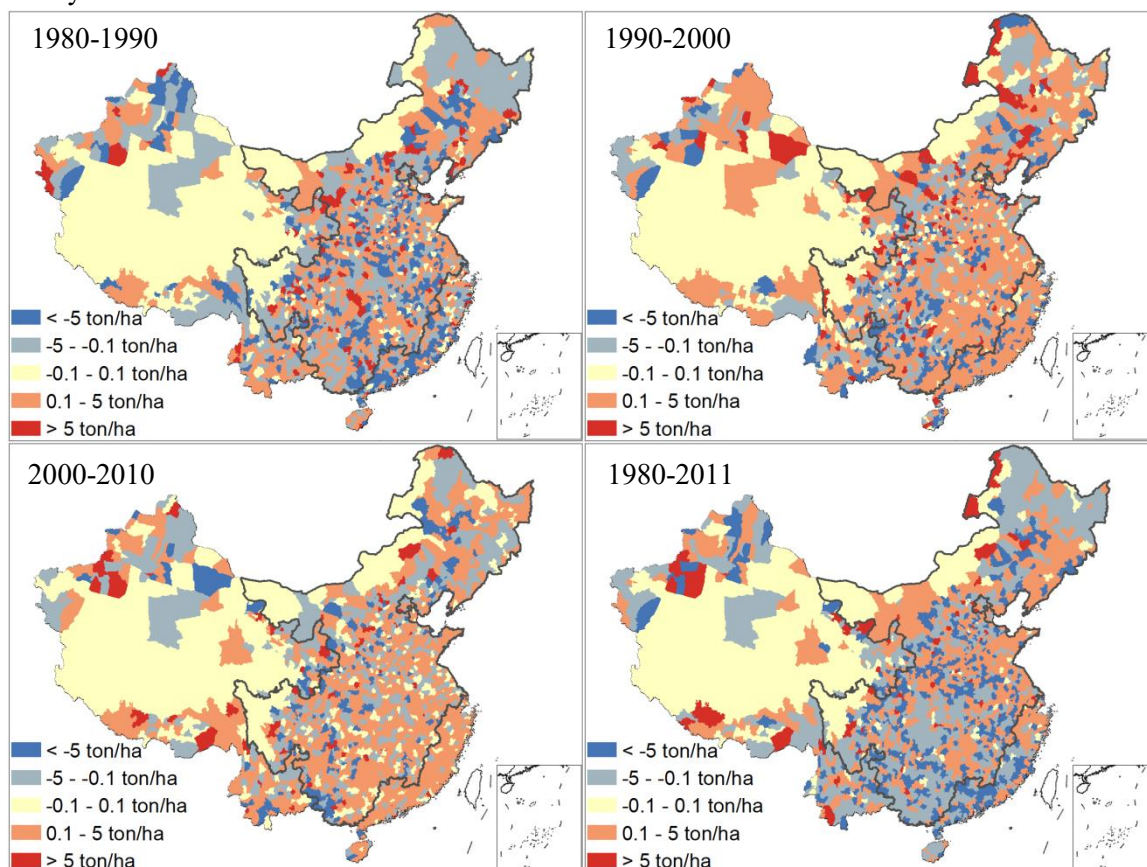
b. Wheat



c. Maize



d. Soybean



A III-4. Estimations from log-log regression with its 95% standard error.

	Rice area	Rice yield	Wheat area	Wheat yield	Maize area	Maize yield	Soybean area	Soybean yield
L.y	0.77	0.32	0.78	0.26	0.69	0.24	0.66	0.28
	[0.72,0.81]	[0.29,0.34]	[0.75,0.81]	[0.25,0.28]	[0.66,0.73]	[0.22,0.26]	[0.62,0.69]	[0.26,0.29]
GDP	-0.0084	0.019	-0.0019	0.013	-0.0059	0.026	-0.0058	-0.017
	[-0.020,0.0034]	[0.011,0.028]	[-0.018,0.014]	[0.0026,0.022]	[-0.024,0.012]	[0.018,0.035]	[-0.025,0.014]	[-0.030,- 0.0042]
Population	0.098		0.089		0.11		0.075	
	[0.046,0.15]		[0.034,0.14]		[0.055,0.16]		[-0.018,0.17]	
Labour	0.057	-0.019	0.021	0.0035	0.014	-0.0055	0.050	-0.0073
	[0.025,0.088]	[-0.036,- 0.0016]	[-0.0092,0.051]	[-0.020,0.027]	[-0.015,0.044]	[-0.024,0.013]	[0.017,0.084]	[-0.028,0.013]
Machinery	0.020	0.015	0.016	0.015	0.022	0.024	0.021	-0.013
	[0.0095,0.030]	[0.0066,0.023]	[0.0033,0.029]	[0.0047,0.025]	[0.0094,0.034]	[0.014,0.033]	[0.0050,0.038]	[-0.026,-0.0013]
Road	-0.075	0.066	0.091	0.02	0.025	-0.00023	-0.077	0.11
	[-0.11,-0.038]	[0.039,0.093]	[0.043,0.14]	[-0.018,0.059]	[-0.019,0.069]	[-0.030,0.030]	[-0.14,-0.010]	[0.051,0.17]
Fertilizer		0.041		0.0091		0.027		-0.029
		[0.028,0.054]		[-0.0018,0.020]		[0.014,0.039]		[-0.044,-0.014]
Rainfall	0.002	-0.020	-0.0056	0.021	0.0092	0.073	0.00088	-0.047
	[-0.022,0.026]	[-0.037,-0.0027]	[-0.025,0.014]	[0.0051,0.038]	[-0.014,0.032]	[0.056,0.090]	[-0.023,0.025]	[-0.075,-0.019]
GDD	0.058	0.091	-0.035	0.095	-0.0072	0.054	0.036	0.063
	[-0.16,0.28]	[0.031,0.15]	[-0.15,0.083]	[0.0013,0.19]	[-0.14,0.13]	[-0.013,0.12]	[-0.097,0.17]	[-0.076,0.20]
WTO	0	-0.018	0	0.028	0	0.022	0	-0.0082
	[0,0]	[-0.027,- 0.0096]	[0,0]	[0.017,0.039]	[0,0]	[0.013,0.031]	[0,0]	[-0.023,0.0064]
Spatial rho	0.093	0.28	0.20	0.31	0.18	0.40	0.24	0.24
	[0.062,0.12]	[0.26,0.31]	[0.18,0.22]	[0.29,0.33]	[0.15,0.21]	[0.38,0.42]	[0.21,0.26]	[0.22,0.25]
Variance	0.11	0.075	0.17	0.14	0.18	0.11	0.23	0.30
sigma2_e	[0.086,0.13]	[0.070,0.080]	[0.15,0.19]	[0.14,0.15]	[0.15,0.21]	[0.10,0.11]	[0.20,0.25]	[0.29,0.31]
R ²	0.947	0.307	0.926	0.293	0.904	0.295	0.861	0.191
AIC	23901.4	9741	50482.4	43428.4	54361.9	30721.1	67690.7	82383.9
BIC	23987.8	9844.7	50570.4	43534	54449.9	30826.7	67779.1	82489.9
N	41788	41788	48701	48701	49042	49042	50995	50995

A III-5. Estimations from standard regression with its 95% standard error.

	Rice area	Rice yield	Wheat area	Wheat yield	Maize area	Maize yield	Soybean area	Soybean yield
L.y	0.77 [0.72,0.81]	0.32 [0.29,0.34]	0.78 [0.75,0.81]	0.26 [0.25,0.28]	0.69 [0.66,0.73]	0.24 [0.22,0.26]	0.66 [0.62,0.69]	0.28 [0.26,0.29]
GDP	-0.011 [-0.02,-0.005]	0.070 [0.041,0.099]	-0.019 [-0.027,- 0.01]	0.036 [0.011,0.062]	-0.0036 [-0.014,0.007]	0.073 [0.049,0.097]	-0.0027 [-0.017,0.011]	-0.041 [-0.071,-0.012]
Population	0.044 [0.021,0.066]		0.043 [0.018,0.067]		0.059 [0.032,0.087]		0.047 [-0.012,0.11]	
Labour	0.026 [0.012,0.040]	-0.047 [-0.09,-0.004]	0.01 [-0.0050,0.025]	0.0098 [-0.034,0.054]	0.0074 [-0.0087,0.023]	-0.017 [-0.056,0.022]	0.036 [0.012,0.059]	-0.014 [-0.049,0.021]
Machinery	0.011 [0.006,0.017]	0.048 [0.022,0.074]	0.006 [-0.0014,0.013]	0.038 [0.013,0.064]	0.017 [0.0087,0.025]	0.062 [0.037,0.087]	0.017 [0.0033,0.030]	-0.029 [-0.06,- 0.003]
Road	-0.028 [-0.036,- 0.02]	0.11 [0.063,0.15]	0.0028 [-0.0090,0.015]	0.026 [-0.022,0.074]	0.0045 [-0.0082,0.017]	-0.0022 [-0.042,0.038]	-0.047 [-0.069,-0.025]	0.11 [0.053,0.17]
Fertilizer		0.16 [0.11,0.21]		0.029 [-0.0039,0.062]		0.084 [0.044,0.12]		-0.077 [-0.12,-0.038]
Rainfall	0.0014 [-0.006,0.008]	-0.033 [-0.06,- 0.005]	-0.0022 [-0.008,0.003]	0.028 [0.007,0.049]	0.0085 [0.001,0.016]	0.10 [0.077,0.13]	0.0022 [-0.0080,0.012]	-0.051 [-0.082,-0.020]
GDD	0.0081 [-0.025,0.041]	0.095 [0.033,0.16]	-0.021 [-0.04,- 0.001]	0.076 [0.0017,0.15]	-0.0018 [-0.027,0.023]	0.046 [-0.011,0.10]	0.0019 [-0.029,0.033]	0.042 [-0.052,0.14]
WTO	0.000078 [-0.002,0.0022]	-0.023 [-0.034,-0.012]	-0.00036 [-0.004,0.003]	0.027 [0.017,0.038]	-0.0003 [-0.003,0.002]	0.023 [0.013,0.032]	-0.012 [-0.017,-0.007]	-0.007 [-0.019,0.005]
Spatial rho	0.097 [0.066,0.13]	0.28 [0.26,0.31]	0.22 [0.19,0.24]	0.31 [0.29,0.33]	0.19 [0.16,0.22]	0.40 [0.38,0.42]	0.24 [0.22,0.27]	0.24 [0.22,0.25]
Variance sigma2_e	0.019 [0.016,0.023]	0.42 [0.39,0.45]	0.035 [0.030,0.039]	0.47 [0.44,0.50]	0.049 [0.041,0.058]	0.41 [0.39,0.43]	0.093 [0.082,0.10]	0.70 [0.68,0.72]
R ²	0.948	0.309	0.93	0.304	0.903	0.278	0.861	0.193
AIC	-47196.6	81417	-26549.2	100672.3	-9657.5	95818.1	22831.2	125451.3
BIC	-47101.6	81512.1	-26452.5	100769.1	-9560.7	95914.9	22928.4	125548.5
N	41788	41788	48701	48701	49042	49042	50995	50995

Chapter IV. Changes in land use efficiency

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Land use efficiency in China's crop production from 1980 to 2011

Abstract

Higher efficiency of land use is particularly important in regions with low per capita land availability. Land is scarce in Chinese agriculture. Improving land use efficiency (LUE) is therefore critical for food security and sustainable agriculture in China. We estimated technical efficiency (TE) and LUE in crop production in China with a spatial autoregressive stochastic frontier approach with county-level data from 1980 to 2011. The results suggest that overall TE increased by 20 % during the study period but varied between regions, with a lower percentage in the northeast and northwest, and a higher percentage in the north and the south. Urbanisation resulted in a lower TE and the greater distance from provincial capitals resulted in a higher TE. The LUE and TE of crop production were positively correlated.

Keywords: spatial spill-over, technical efficiency, land use efficiency, spatial autoregressive stochastic frontier model

JEL: O13, Q15, Q24, R24

1. Introduction

Cropland expansion and input-based intensification has led to the deterioration of natural environment and ecosystems, such as deforestation, soil degradation, and water pollutions (Delzeit et al., 2017). Meanwhile, inevitable urban expansion, one fundamental aspect of urbanization, would result in global cropland loss (D'Amour et al., 2017). Rapid economic growth and urbanisation are leading to large-scale urban land expanding and cultivated land being lost, resulting in a substantial change in consumption patterns and diet structure (Alexander et al., 2015; Godfray et al., 2018; Springmann et al., 2018). For a sustainable and food-secure future, therefore, high yield and high efficiency are needed to substantially reduce the environmental footprint of crop production. Technical efficiency (TE) is the indicator for the production performance with which current inputs is used to produce crops. Land use efficiency (LUE) measures how efficient use of cropland, as an input factor, is used in crop production comparing to the best-practice frontier. LUE indicates the performance of land use, which is defined as the ratio between optimum land area for observed output and observed land area; a higher score of LUE implies a lower gap between the optimal use of the land area and the observed use of the land area, which can be seen as an indicator for a better use of land. Increasing LUE leads to higher TE and enhance sustainability of agricultural production (Foley et al., 2011; Zhang et al., 2018).

China is a country with fast growing food demand, due to population growth and dietary structure shift, and limited land and water resources (Zhu et al., 2019). Improvement in the LUE and TE of crop production is crucial if China is to feed 19 % of the global population with just 9 % of the world's arable land (FAO, 2019). In past decades in China, a higher TE has been achieved through intensive use of inputs, such as increased usage of irrigation (Zhu et al., 2013) and fertilisers (Huang and Jiang, 2019). However, it is unsustainable for TE of crop production to increase at the expense of sensitive ecosystems and for input use to further rise. Numerous studies have analysed the TE of agricultural production in China using stochastic frontier analysis (Brümmer et al., 2006; Ma et al., 2010) and Data Envelopment Analysis (DEA) (Monchuk and Chen, 2008; Yang et al., 2017).

However, heterogeneous biophysical conditions such as soil type, topography, climate and hydrological conditions, determine much of the spatial patterns in agricultural production activities (Grau et al., 2013). This leads to spatially distinct differences in agricultural production efficiency (Neumann et al., 2010). For example, Yang (1996) found a spatial variation in the factor productivities of maize production due to natural conditions, while Chen et al. (2009) estimated agricultural production with fixed effects captured by village

dummies. But few applications have taken the spatial spill-over of agricultural production into account which may lead to biased and inaccurate estimations.

Studies on spatial stochastic frontier models have developed rapidly in recent decades. The main models accounting for spatial dependence in frontier analysis can be divided into two major groups: those that explain inefficiency/efficiency in terms of exogenous determinants analysing heterogeneity and those that account for spatial dependence by including a spatial autoregressive specification in the model (LeSage and Pace, 2009). The first study estimated a spatial error production frontier panel model in rice farming (Druska and Horrace, 2004), calculating the time-invariant technical inefficiency, and concluded that spatial correlation affects TE. Cho et al. (2010) analysed the TE for agricultural performance in China using spatial lag models with county-level datasets, and Jiang et al. (2017) introduced spatial dependency to the determinants of a single-factor efficiency model with provincial data for the period 2003 to 2011. Pede et al. (2018) investigated the role of spatial dependency of dependent variable in the technical efficiency estimation of rice farmers using panel data in the Philippines, and established that the preferred option was the spatial autoregressive stochastic frontier model (SAR-SFA) comparing with non-spatial spill-over. In their model, spill-overs are adopted explicitly and are related to the independent variables (LeSage and Pace, 2009). Glass et al. (2016) proposed a SAR-SFA for panel data and also introduced the concept of efficiency spill-over. Besides, their term for technical inefficiency is homoscedastic, which they applied to aggregate production in Europe. Ramajo and Hewings (2018) developed a SAR-SFA model with the feature of a time-varying decay efficiency specification, which was used to estimate regional development performance in western Europe. Most recently, Tsukamoto (2018) constructed a SAR-SFA model that simultaneously estimates the determinants of technical inefficiency, applied to the Japanese manufacturing industry, and claimed that a stochastic frontier model with a spatial lag structure and introducing a model of technical inefficiency estimates parameters correctly.

To the best of our knowledge, there has been no empirical analysis of the change in and determinants of TE for agricultural production in China using long-term county-level data and accounting for spatial spill-over. To bridge the gap, we present the first empirical analysis of a spatial autoregressive stochastic model to estimate the TE of agricultural production and LUE in China at county level from 1980 to 2011. A SAR-SFA model was developed by extending the approach of Greene (2005) to measure the TE of agricultural

production in China and simultaneously estimate the determinants of technical inefficiency. Our research questions are:

How the TE of crop production changes during 1980 to 2011?

What are the determinants of TE?

How LUE varied over time and space?

Our aim is to shed light on efficiency pathways by analysing how the TE of agricultural production varied spatially and temporally, paying particular attention to the partial efficiency of cropland, i.e. LUE. Identification and analysis of the effects of these determinants could help design policies to improve agricultural land use and enhance TE in agricultural production.

2. Methodology

The contribution made by the spatial autoregressive stochastic frontier model was extended by true fixed effects based on the balanced panel data (Glass et al., 2016). The process of estimating SAR-SFA models includes four steps: 1) estimate the production function and technical inefficiency model to obtain coefficients and determinants of technical inefficiency in agricultural production; 2) derive TE and technical inefficiency (TIE) scores; 3) Calculate the elasticity with the parametric estimation of the translog production function; 4) finally, quantify the LUE based on the estimates from step 1 and the technical inefficiency scores from step 2.

2.1 The spatial autoregressive frontier model

We used the translog production function to study agricultural production behaviour. This production function is more flexible and imposes few assumptions on the functional form and its elasticities (Christensen et al., 1973). As featured in the literature (Ramajo and Hewings, 2018), a Hicks-neutral technical change was assumed and a linear time trend variable t and its square t^2 added in production function in Equation 1, with the parameters η . The number of inputs is 5. Empirically, the model was specified as follows:

$$\begin{aligned} \ln y = & \alpha + \rho W \ln y + \eta_1 t + \eta_2 t^2 + \sum_{i=1}^5 \beta_i \ln x_i + \frac{1}{2} \sum_{i=1}^5 \sum_{j=1}^5 \beta_{ij} \ln x_i \ln x_j + v - u; \quad i = 1, \dots, 5; j \\ & = 1, \dots, 5 \end{aligned}$$

Equation 1

where y is the output vector as a function of the input vectors x , and β_i are unknown parameters to be estimated for inputs x_i . β_{ij} are parameters for trans-input, which is assumed to be $\beta_{ij} = \beta_{ji}$ for any inputs. And we use Lny and Lnx to present the natural log of y and x . $(v - u)$ is the error term, which has two components (Aigner et al., 1977; Meeusen and van Den Broeck, 1977). v is set to capture noise, accounting for random effects, which is assumed to be independent and identically distributed (*i.i.d.*), $v \sim i.i.d.N(0, \sigma_v^2)$. u is set to be the technical inefficiency term, which includes non-negative random variables and is often assumed to be independently distributed, $u \sim i.i.d.N(\mu, \sigma_u^2)$. W is the spatial weight matrix, an $n \times n$ matrix of pre-specified non-negative constants that describes the spatial arrangement of the cross-sectional units and the strength of the spatial interaction between n units. It represents the spatial structure of the data. The most common practice is to treat it as non-stochastic. All results are conditional upon the specification of W (Dubin, 1998; Pace et al., 1998). $W = (w_{ij}, i, j = 1, \dots, n)$ and w_{ij} , the elements of the matrix, typically reflect the “spatial influence” of unit j on unit i . All the elements on the main diagonal of W were set to zero to exclude “self-influence” by assuming $w_{ij} = 0, \forall i = j$ so that W has a zero diagonal.

A reduced form of Equation 1 was used:

$$\text{Lny} = (I - \rho W)^{-1} \left\{ \alpha + \sum_{i=1}^5 \beta_i \text{Lnx}_i + \frac{1}{2} \sum_{i=1}^5 \sum_{j=1}^5 \beta_{ij} \text{Lnx}_i \text{Lnx}_j + v - u \right\}$$

Equation 2

Based on the estimates of the above production function, the elasticity of output with respect to input could be interpreted as the sensitivity of the input variables for crop production. We estimate the elasticity of inputs by calculating the marginal effects (Elhorst, 2014; LeSage and Pace, 2009):

$$\varepsilon_{x_i} = \frac{\partial \text{Lny}}{\partial \text{Lnx}_i} = (I - \rho W)^{-1} \left\{ \beta_i + \sum_{j=1}^5 \beta_{ij} \text{Lnx}_j \right\}$$

Equation 3

Since the elasticity of each input factor depends on the other input factors, elasticities could be interpreted as no longer being fixed and identical for all the individuals and periods. Moreover, every diagonal element of the matrix W refers to its own explanatory variable,

i.e. a direct effect, and every non-diagonal element refers to its neighbour's explanatory variable, i.e. an indirect effect (Glass et al., 2016; Tsukamoto, 2018).

2.2 Technical efficiency and determinants model

Efficiency analysis consists of two parts: the estimation of the variation across observations and the determinants of efficiency (Battese and Coelli, 1995). The estimation of TE model is a common way of evaluating the performance of crop production and offers an explanation of technical efficiency in crop production. TE is defined as:

$$TE = \frac{y}{y^{opt.}} = e^{-u}$$

Equation 4

where y is the observed output and $y^{max.}$ is the optimal output (Farrell, 1957). As the technical inefficiency component is heteroscedastic, it accounts for the determinants of efficiency in the estimation (Kumbhakar and Lovell, 2003). Technical inefficiency may depend on economic development, the climate situation and the location, which are described in the “Data” section. The technical inefficiency model referred to in Equation 1 is written as:

$$u = \tau_0 + \sum_{m=1}^M \tau_m z_m, m = 1, \dots, M$$

Equation 5

Where $z_m (N \times T)$ is a vector of explanatory variables associated with technical inefficiency and M is the number of such variables. τ_m is the estimated parameter for each explanatory variable.

2.3 Land use efficiency

LUE is derived from environmental efficiency as the ratio of optimal amount feasible to observed use of an environmentally detrimental input, given technology and the observed levels of output and conventional inputs (Reinhard et al., 1999). The LUE defined here can also be interpreted as partial efficiency of land use, which is the ratio of the optimal land area needed for the observed production to the observed land area use (Huang et al., 2016; Reinhard et al., 2002):

$$LUE_t = \frac{\text{optimal land area}_t}{\text{observed land area}_t}$$

Specifically, x_3 is the land use area in this paper, thus x'_3 refers to the optimal land input:

$$\ln LUE = \ln \left(\frac{x'_3}{x_3} \right) = \ln x'_3 - \ln x_3$$

Equation 6

Setting $u=0$ and letting the output of the land use efficient producer equal to that in Equation 1 (Reinhard et al., 2002) gives:

$$\begin{aligned} \ln y = & \alpha + \rho W \ln y + \beta_3 \ln x'_3 + \frac{1}{2} \beta_{33} \ln x'_3 \ln x'_3 + \beta_{13} \ln x_1 \ln x'_3 + \beta_{23} \ln x_2 \ln x'_3 \\ & + \beta_{34} \ln x'_3 \ln x_4 + \beta_{35} \ln x'_3 \ln x_5 + \sum_{i \neq 3}^5 \beta_i \ln x_i + \frac{1}{2} \sum_{i \neq 3}^5 \sum_{j \neq 3}^5 \beta_{ij} \ln x_i \ln x_j + v \end{aligned}$$

Equation 7

The logarithm of the stochastic land input efficiency measure ($\ln LUE = \ln x'_3 - \ln x_3$) can be isolated. Setting Equation 1 and Equation 7 as equal yields:

$$\begin{aligned} & \frac{1}{2} \beta_{33} (\ln x'_3 \ln x'_3 - \ln x_3 \ln x_3) \\ & + (\beta_3 + \beta_{13} \ln x_1 + \beta_{23} \ln x_2 + \beta_{34} \ln x_4 + \beta_{35} \ln x_5) (\ln x'_3 - \ln x_3) + u \\ & = 0 \end{aligned}$$

and it can then be solved for $\ln LUE$ to obtain:

$$\ln LUE = \frac{-(\beta_3 + \sum_j^5 \beta_{3j} \ln x_j) \pm \sqrt{(\beta_3 + \sum_j^5 \beta_{3j} \ln x_j)^2 - 2\beta_{33}u}}{\beta_{33}}$$

Equation 8

Land use efficiency was calculated using the positive root in Equation 8 (Reinhard et al., 1999, 2002).

3. Data

We use data derived from China Statistic Yearbooks and Chinese Agricultural Statistic Yearbooks from 1980 to 2011. The balanced panel data used in this study cover 2007 counties in China for the period 1980-2011 at three-year intervals. We removed counties in provinces with little cropland when the average cropland area between 1980 and 2011 was below 10,000 ha and accounted for less than 10 % of the total provincial area (A IV-1). We calculated all the variables were obtained on the basis of a three-year moving average to

smooth out short-term fluctuations and to highlight longer-term trends. For the estimation, variables' values are log-transformed and then normalised around the relevant sample mean to reduce the influence of unit changes. To account for the inflation and make monetary values comparable over time, all the variables related to monetary values in different years were converted using the constant price in 2010.

3.1 Output and input variables

The output variable was the real cropping output value of a county in RMB (Chinese Yuan) (y). This output value comes from crop production and denotes the quantity of production multiplied by consumer prices in the year. The inputs included the amount of agricultural labour (x_1), machinery power in agriculture (x_2), land (sown area x_3), fertiliser (x_4) and pesticide (x_5) (Coelli and Rao, 2005). Labour (x_1) was the amount of labour for farming activities. Machinery (x_2) referred to total horsepower of agricultural machinery used on farms in order to reduce the bias of different sizes of machine, covering the machines in harvesting, irrigation, transportation and so on. Land (x_3) was the total sown area for all annual crops including grain, oil, cotton, sugar crops, vegetables and melons, fibre crops, medicine crops and other crops. It is harvested area and would be recalculated when the land was under temporary crops (double-cropped areas were counted twice). The sown area (x_3) reflected the effective usage of cultivated land in agriculture, because particularly in the Middle-Lower Yangtze River Valley, in the south and southwest of China, the multiple cropping index is greater than one (Hou et al., 2012). Fertiliser (x_4) was measured as the annual consumption quantity of chemical fertiliser (nitrogen, phosphorus, potassium and potash contained in combined fertilisers) used for farming. Pesticide (x_5) is the annual consumption quantity of pesticides. The detailed descriptive statistics for the continuous variables used here are presented in Table IV-1.

Table IV-1. Variables and summary statistics.

Variable description	Unit	Symbol	Mean	Std.	Min.	Max.
<i>Variables in the production function</i>						
Output - farming output value	10 ⁶ Yuan	y	747	768	0	8,819
Input - agricultural labour	10 ³ Person	x_1	151	113	0	1,013
Input - machinery power in agriculture	10 ⁶ Watt	x_2	209	253	0	3,049
Input - sown area	10 ³ ha	x_3	69	51	0	405
Input - fertiliser	10 ³ ton	x_4	17	19	0	250
Input - pesticide	10 ³ ton	x_5	1	8	0	362
<i>Variables in the technical inefficiency model</i>						
Population	10 ³	z_1	535	408	3	7,682
Urbanisation rate	%	z_2	18	17	0	97
Elevation	m	z_3	614	774	0	4,512
Suitable soil for farming	10 ³ ha	z_4	75	88	0	927
Road length	km	z_5	80	68	5	1,343
Distance to nearest provincial capital	km	z_6	143	93	0	759
Livestock output value	10 ⁶ Yuan	z_7	414	535	0	7,712
Forestry output value	10 ⁶ Yuan	z_8	55	81	0	1,976
Temperature	°C	z_9	14	5	-4	24
Accumulated temperature over 10 degrees (growing degree days - GDD)	°C	z_{10}	499	143	40	889
Rainfall	mm	z_{11}	1000	471	23	2,979

3.2 Technical inefficiency determinants

The technical inefficiency effects in the stochastic frontier were related to social economic variables, ecological considerations and climate factors. The socio-economic variables included population (z_1), urbanisation (z_2), roads length (z_5), livestock output values (z_7) and forestry output values (z_8). The total population of a county (z_1) – one of the important county-specific factors for demand where a large and ever-growing population means the law of diminishing returns is in operation as more labour is applied to shrinking parcels of land (Yao and Liu, 1998) – will consequently influence TE in agricultural production. The urbanisation rate (z_2) was calculated as the urban population divided by the total population to clarify the development driving new agronomic techniques (Masters et al., 2013). The mean of the population and the urbanisation rate were 535 thousand people and 18 % respectively. Road length (z_5) was the length of all roads in the county, including national-level, provincial-level and county-level paved roads, to show the development of transportation and market access. Livestock output value (z_7) and forestry output value (z_8) were another two activities in agricultural production. Their development may

promote agricultural practices for intensifying production sustainably and thus have an influence on efficiency (Alves et al., 2017).

To capture the ecological and climate conditions, we included elevation (z_3), soil quality (z_4), temperature (z_9), accumulated temperature over 10 degrees (z_{10}) and rainfall (z_{11}). The elevation median (z_3) was devised from the global digital elevation model (DEM), i.e. a digital representation of ground surface topography or terrain. DEM and county boundaries were combined to summarise the median elevation of each county. Land area with suitable soil for farming (z_4) was intercepted for China from global Soil and Terrain Database (SOTER), v1.0. The soil information was interpreted and divided into suitable and unsuitable categories. The more the suitable area, the better soil quality for crop. Climatic variables influence the performance of agricultural production, for example rainfall will have an impact on irrigation (Bokusheva, 2005; Demir and Mahmud, 2002). The data for annual average temperature (z_9), accumulated temperature over 10 degrees (also called Growing Degree Days (GDD), z_{10}), and rainfall (z_{11}) were from China's meteorological administration. To represent accessibility, we accounted for distance to the nearest provincial capital (z_6). It is the straight line distance to the nearest provincial capital.

3.3 Spatial weight matrix

The spatial weight matrix captures the spatial arrangement and spatial interaction between units. In practice, the commonly used spatial weight matrices are based on distance, boundaries adjacency or a combination of two. Here we use the first-order queen contiguity weights with row-normalised matrix elements, as boundary sharing between spatial units plays an important role in determining the degree of spatial influence. The queen weighting matrix considers all neighbours that share a common boundary or connect via a vertex point. The ij^{th} component in the matrix W equals 1 if units i and j share the same part of the county boundary and $i \neq j$, otherwise the elements are equal to 0, and the diagonal elements of W are set to zero because an observation cannot, by definition, be a neighbour to itself. The values are then normalised so that each row of weight matrix sums to 1, and all neighbours have the same weight, so that the endogenous spatial lag of the dependent variable is a simple average of observation values for the dependent variable of neighbouring counties, which preserves the scaling of the data.

4. Results

Prior to the model estimations, we conducted tests to determine the suitable econometric model specification. We use the Hausman test to verify if a fixed-effects model or a random-effects model is appropriate, and we employ the likelihood ratio test to assess whether to choose the Cobb-Douglas production function or the translog production function, and we also use the likelihood ratio test to improve the technical inefficiency model specification and spatial dependence. The tests and explanations can be found in Appendix (A IV-2).

4.1 Parametric estimates of the spatial autoregressive frontier function

The estimation results of SAR-SFA with fixed effects are presented in Table IV-2. The estimated first-order coefficients for the inputs labour (x_1), machinery (x_2), land (x_3), fertiliser (x_4) and pesticide (x_5) had the expected positive signs, with 0.059, 0.046, 0.25, 0.097 and 0.01 respectively. As the output and input variables were normalised by sample means, the estimated first-order parameters can be interpreted as production elasticities at the sample mean (Kumbhakar and Lovell, 2003). In terms of the magnitude of coefficients, the most important input for production was land (x_3), followed by fertiliser (x_4), machinery (x_2), labour (x_1) and pesticide (x_5). This shows the essential role of land input in crop production, consistent with the observation that land is scarce in China (Chen et al., 2009; Ma et al., 2010; Yao and Liu, 1998). Land is a natural resource for all human production and living activities, including agriculture, and its supply is fixed (Jin et al., 2018). The recent developments in China's land policy are pushing agricultural production towards larger scales to boost productivity further. Growth in land input was due to the expansion and intensification (e.g. multiple cropping) of cultivated land. However, limited land resource and decreasing multiple cropping in many regions has been witnessed in China (Yan et al., 2009). In other words, the efficient utilisation of China's scarce land resource is vital. Fertiliser, as the traditional input, is the second most important input in crop production on average. To get more output, fertiliser becomes the first choice since land resource is limited. Machinery is more important than labour averagely. However, the electricity changes over time and regions.

Table IV-2. Estimation of spatial autoregressive production function and technical inefficiency.

Estimates for spatial autoregressive production function				Estimates for technical inefficiency model			
Dependent variable: ln(y)				Dependent variable: inefficiency relevant variable			
Parameters		Coeff.	Confidence intervals	Parameters		Coeff.	Confidence intervals
t	η_1	0.0023	[0.0012,0.0034]	lnz1	τ_1	0.680	[0.60,0.77]
t2	η_2	0.0013	[0.0012, 0.0013]	lnz2	τ_2	0.120	[0.082,0.17]
lnx1	β_1	0.059	[0.037, 0.081]	lnz3	τ_3	-0.120	[-0.15,-0.098]
lnx2	β_2	0.046	[0.032, 0.059]	lnz4	τ_4	-0.0093	[-0.042,0.023]
lnx3	β_3	0.250	[0.22, 0.28]	lnz5	τ_5	-0.045	[-0.13,0.043]
lnx4	β_4	0.097	[0.081, 0.11]	lnz6	τ_6	-0.16	[-0.21,-0.11]
lnx5	β_5	0.010	[0.0028, 0.018]	lnz7	τ_7	-0.95	[-1.00,-0.90]
lnx1lnx1	β_{11}	0.015	[-0.00086, 0.031]	lnz8	τ_8	-0.28	[-0.31,-0.24]
lnx2lnx2	β_{22}	0.0097	[0.0039, 0.015]	lnz9	τ_9	-0.230	[-0.39,-0.068]
lnx3lnx3	β_{33}	0.064	[0.051, 0.076]	lnz10	τ_{10}	-1.28	[-1.55,-1.02]
lnx4lnx4	β_{44}	0.0021	[-0.0089, 0.013]	lnz11	τ_{11}	1.010	[0.89,1.14]
lnx5lnx5	β_{55}	-0.00047	[-0.0042, 0.0033]	_cons	τ_0	-3.510	[-3.59,-3.43]
lnx1lnx2	β_{12}	-0.046	[-0.059, -0.032]	Vsigma			
lnx1lnx3	β_{13}	0.035	[0.020, 0.049]	_cons	ν	-3.88	[-3.93,-3.82]
lnx1lnx4	β_{14}	-0.0024	[-0.017, 0.012]				
lnx1lnx5	β_{15}	0.016	[0.0076, 0.024]				
lnx2lnx3	β_{23}	0.027	[0.011, 0.042]				
lnx2lnx4	β_{24}	-0.0087	[-0.018, 0.00031]				
lnx2lnx5	β_{25}	0.014	[0.0076, 0.020]				
lnx3lnx4	β_{34}	0.00057	[-0.014,0.015]				
lnx3lnx5	β_{35}	-0.039	[-0.048,-0.029]				
lnx4lnx5	β_{45}	0.0086	[0.0026,0.015]				
Spatial lag	ρ	0.520	[0.51,0.53]				

Note: 95 % confidence intervals in brackets

Model performance statistics

AIC	7570
BIC	23918.6
Likelihood value	-1742
Observation number	22077

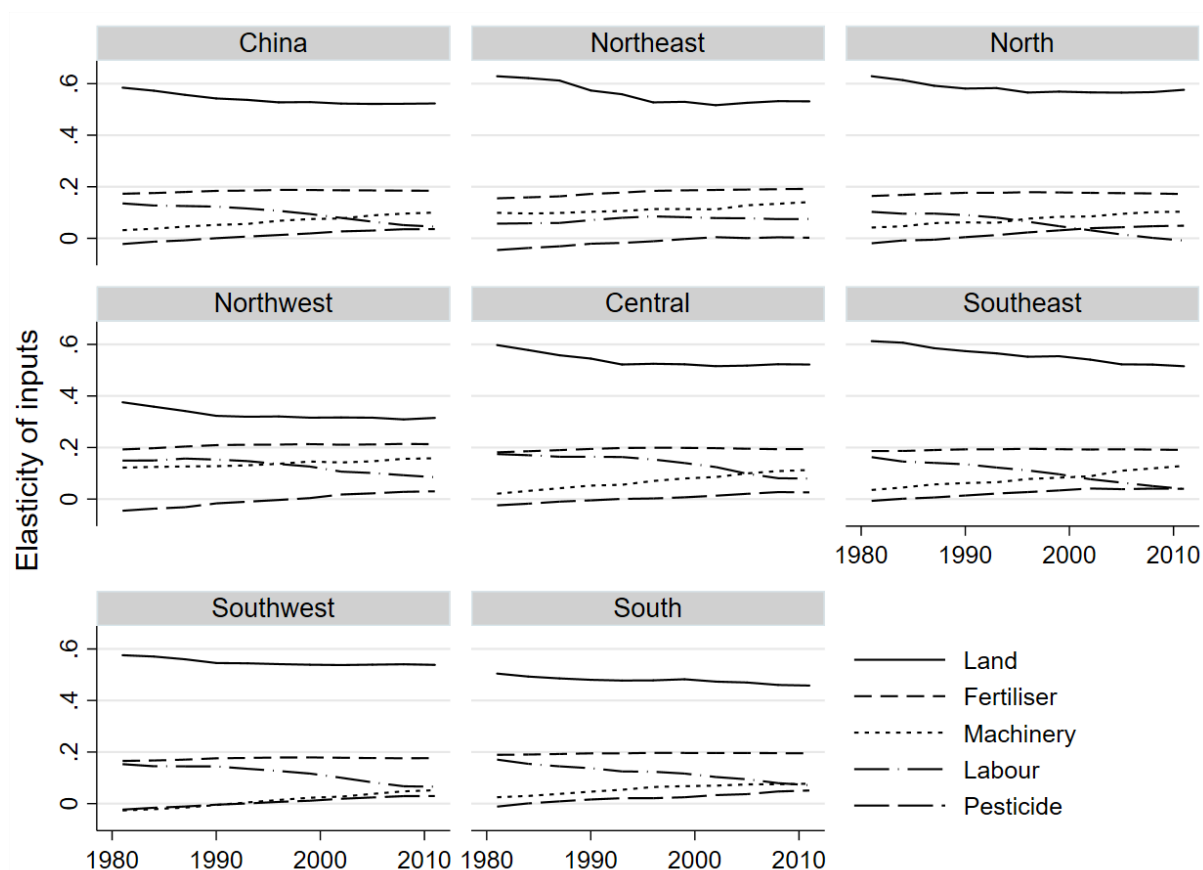


Figure IV-1. Annual elasticities from 1981 to 2011 with respect to inputs in whole China and regions.

The estimated coefficient of spatial lag ρ for the dependent variable was 0.51 and positive, showing that agricultural production has substantial spill-over effects. Moreover, the patterns of production elasticities of inputs are spatial heterogeneous with respect to the output (Equation 3). The time trend by region suggests that the most important input was land, followed by fertiliser, machinery, labour and pesticides (Figure IV-1). Similar to the results of Fan (1997) and Gong (2018), our results for all of China confirm that inputs of land and labour decreased by 0.4 % and 5.9 % respectively, from 1981 to 2011, while the modern inputs of fertiliser, machinery and pesticides increased by 0.2 %, 2.1 % and 1 % respectively. The decline labour is particularly visible in the global model for all of China, but also in all regions, except in the Northeast. In the south and southwest, labour still plays a larger role than machinery as the terrain is dominated by hilly landscape in those regions. Overall, from the similar trends of elasticities, land seems to continue to play a dominant role in agriculture, while machinery has already exceeded labour and will catch up with fertiliser in the future.

4.2 Estimates of technical inefficiency model

Population (z_1), urbanisation (z_2) and rainfall (z_{11}) were found to have positive effects on technical inefficiency, negative influence on TE. A 1% increase of population results in a decrease of the TE in crop production by 0.68 %. A 1 % increase in urbanisation would lead to a 0.12 % decline in TE. The impact of population and urbanisation can be explained by the expansion of the construction area encroaching on farmland (Li et al., 2014; Liu et al., 2014). In addition, they indicate externalities of industrialisation, such as air and groundwater pollution, affecting agricultural production (Monchuk et al., 2010). The coefficient of rainfall (z_{11}) suggests that 1% more rainfall may decrease TE by 1%.

The climate factors of temperature (z_9) and growing degree days (z_{10}) had positive influences on the TE score: a 1% increase each in temperature and growing degree days would increase TE by 0.23 % and 1.28 % respectively. Compared with rainfall, a temperature increase, especially during the growing seasons, had a positive impact on agricultural production. The influence of geographic factors on technical inefficiency was negative but relatively small, at less than 0.2 %, including elevation (z_3 ; 0.12), suitable soil for farming (z_4 ; 0.01), road length (z_5 ; 0.04) and distance to the nearest provincial capital (z_6 ; 0.16). Meanwhile, developing another part of agriculture besides crop farming, such as a 1% increase in forestry (z_7) and livestock (z_8) output, would also lead to a higher TE of 0.95 % and 0.28 % respectively. Furthermore, the development of integrated agriculture with cropping, forestry, fishery and livestock will not only increase farming productivity but sustainable agriculture as well (Huang and Jiang, 2019; Jun and Xiang, 2011).

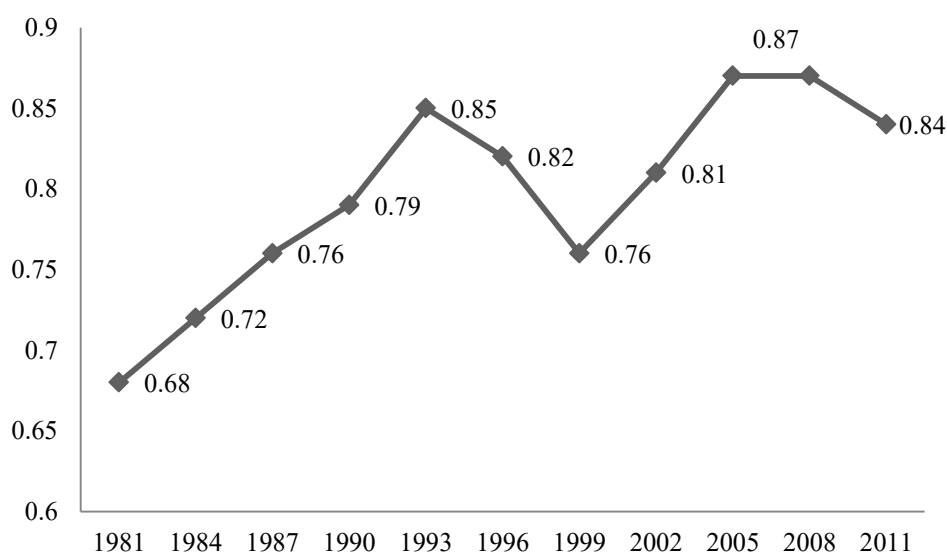


Figure IV-2. Technical efficiency change from 1981 to 2011.

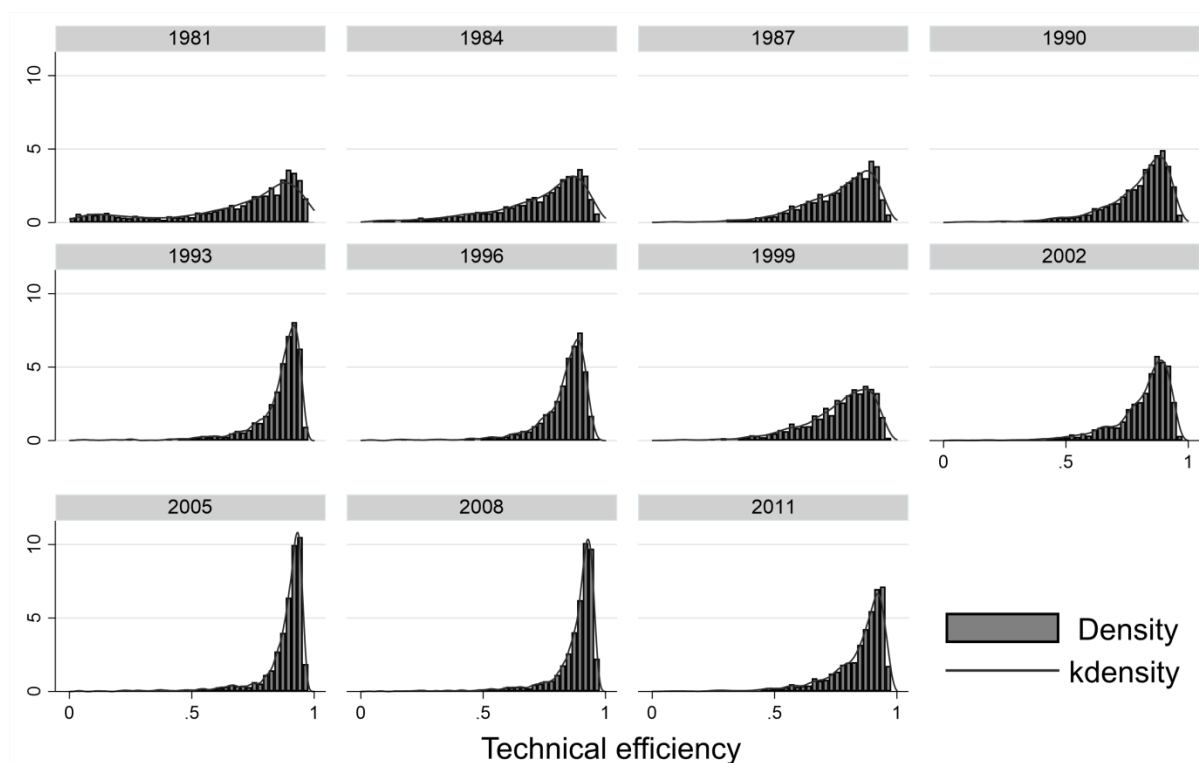


Figure IV-3. Densities of technical efficiency.

Based on the estimated parameters and production function, the TE was obtained for each county in each year. The overall TE was 0.8 on average. During the study period, TE increased from 0.68 to 0.84 while its growth rate decreased (Figure IV-2 and Figure IV-3). The standard deviations of TE reduced during this period, falling from 0.27 to 0.12, which could be interpreted as the regional gap decreasing. For each year, TE was negatively skewed towards converging during the period from 1980 to 2011. The TE of crop production also varied between regions (Figure IV-4), where the TE in the provinces of Shandong, Sichuan, Chongqing, Fujian and Guangxi was greater than 0.86, while in Heilongjiang, Jilin, Shanxi and Shaanxi it was below 0.8. One reason for the lower TE in the northeast, including Heilongjiang and Jilin, would be that large tracts of unused wetland and unused barren land were converted to cultivated land (Hou et al., 2012). Since TE has a tendency to converge across regions and over time, a lower efficiency level signifies a greater potential and a lower cost to increase productivity through improved TE (Ma and Feng, 2013). Therefore, regions such as the northeast part including Heilongjiang, Jilin and Liaoning with low efficiency were more likely to boost efficiency to improve their crop productivity.

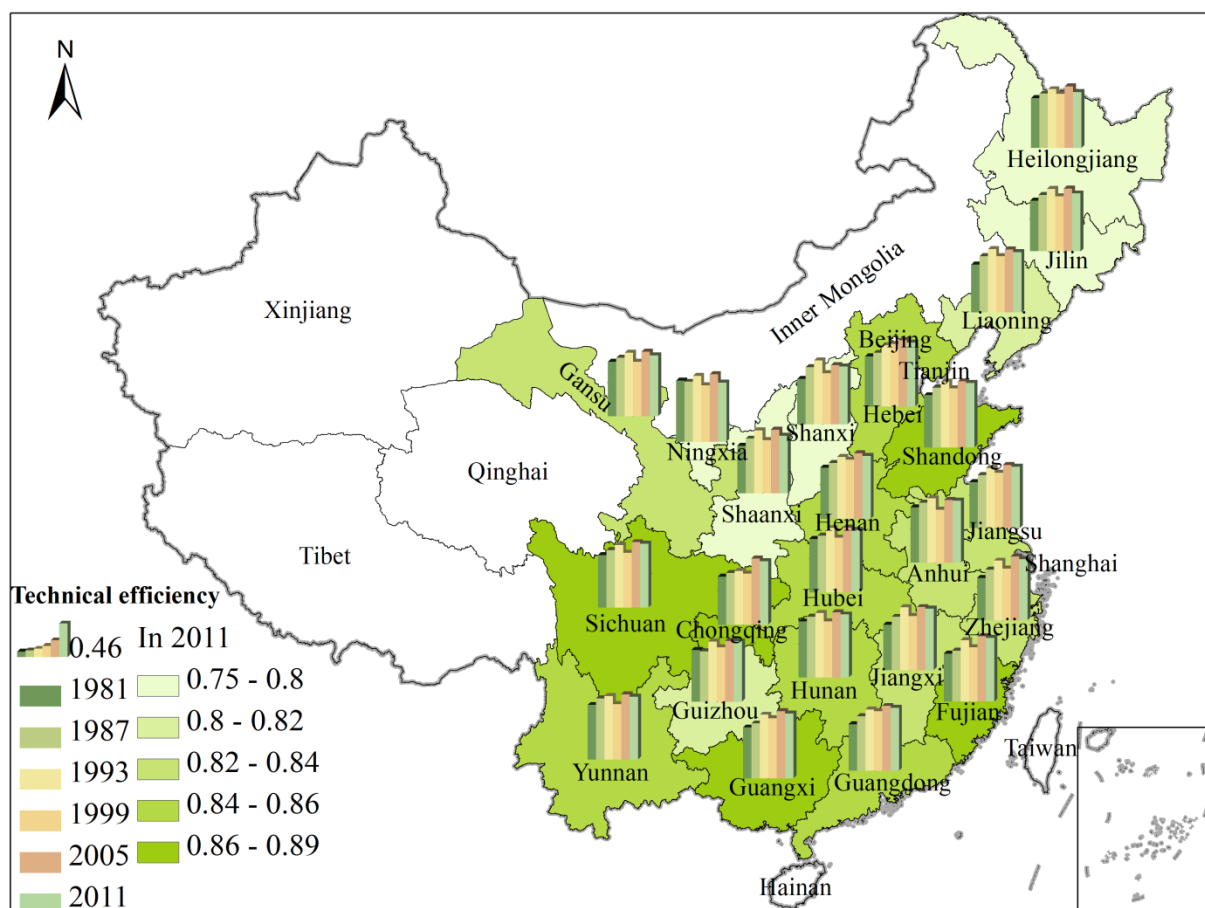


Figure IV-4. Spatial distribution of technical efficiency in 2011 and trends in each province.

4.3 Land use efficiency analysis

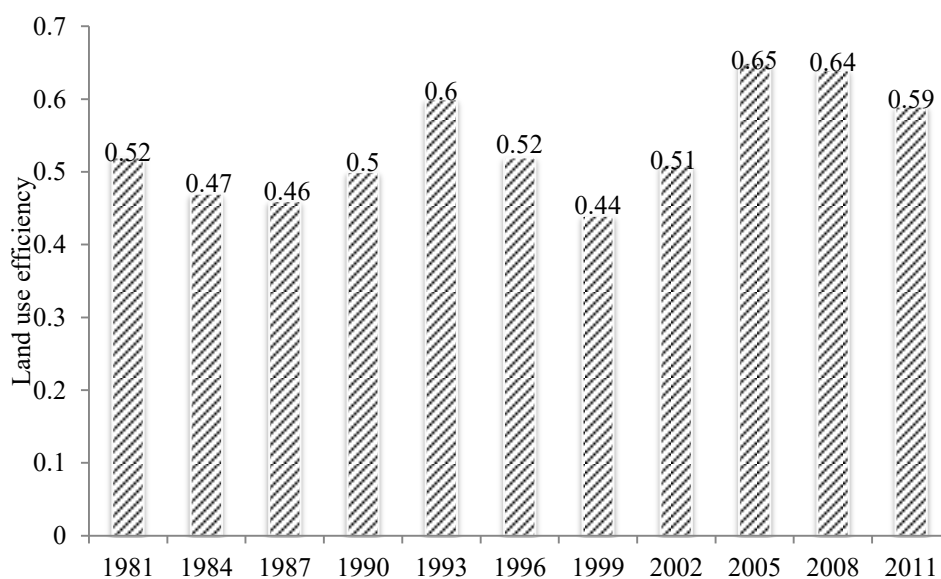


Figure IV-5. Annual changes in land use efficiency.

Our results for LUE suggested an average LUE was 0.54, which was very low (Figure IV-5). The trend also varied greatly over time, ranging from 0.52 in 1980 to 0.59 in 2011.

In 2005 and 2008, it exceeded 0.6, while in 1999 it was only 0.44. Overall, LUE increased slightly, but remained much below 1.

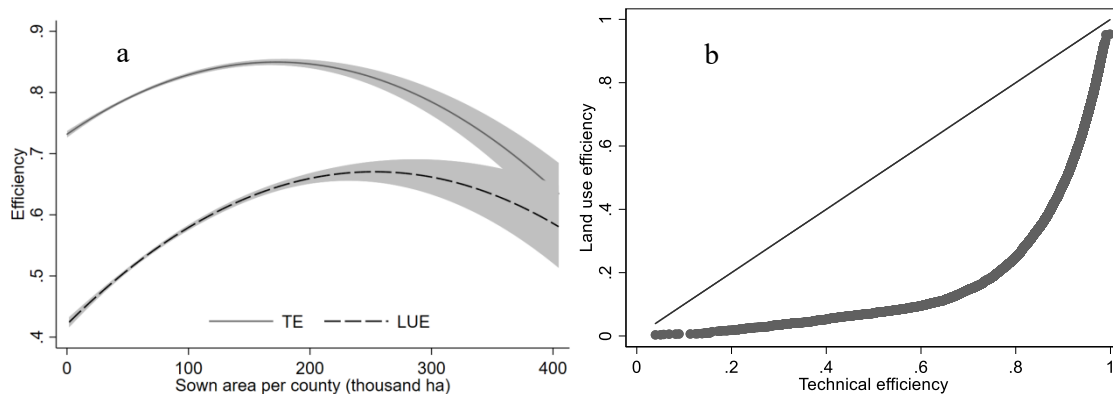


Figure IV-6. Relationship between the sown area and technical efficiency (TE) and land use efficiency (LUE) (a), and the quantile-quantile plot between TE and LUE (b).

The relationship between the sown area and TE and between the sown area and LUE reveals that counties with more than 200,000 ha of sown area had higher variations of TE and LUE (Figure IV-6a). However the counties with a larger sown area were likely to be more efficient than those with a smaller area, which coincides with the results of Zhang et al. (2018). Furthermore, TE and LUE were positively correlated (Figure IV-6b). Consequently, increasing LUE could be taken measurements to ensure TE, especially when LUE was below around 0.2. In a further analysis of LUE, Shandong and Chongqing had the highest LUE at 0.61 on average from 1980 to 2011, while Gansu had the lowest value at 0.41. Jiangsu, Anhui, Henan and Shandong are the main breadbaskets of China and their LUE was relatively high, at above 0.55. However, the LUE of Heilongjiang, also an important breadbasket, was just 0.51.

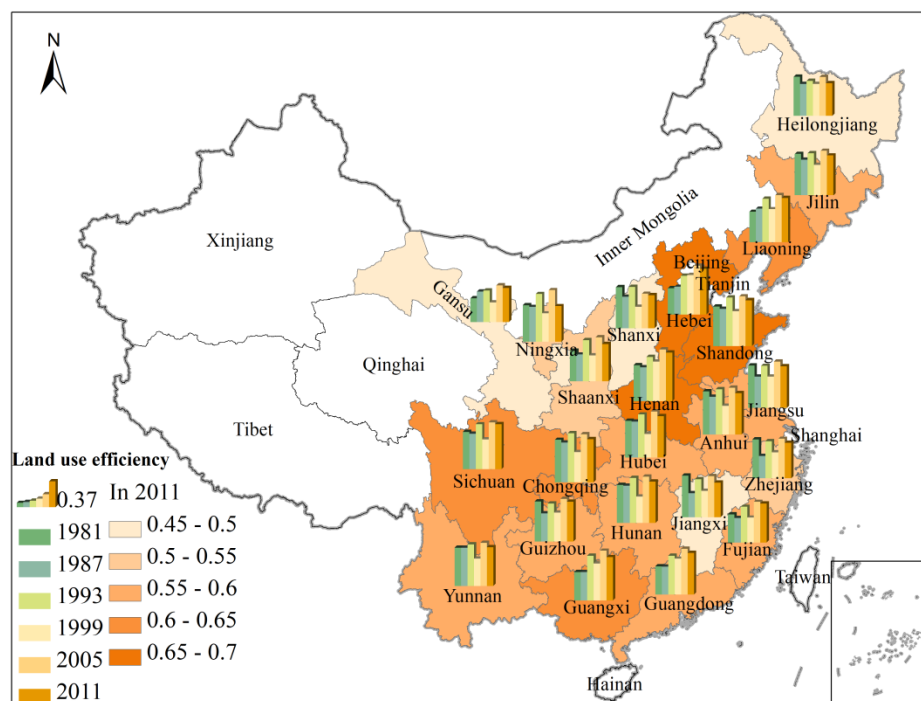


Figure IV-7. Distribution of land use efficiency.

The distribution of LUE in 2011 reveals low LUE in Gansu province (below 0.5) and in Heilongjiang province (lowest with 0.46), but both with an increasing trend (Figure IV-7). LUE of Jiangxi and Shanxi were also below 0.5. Areas with a low LUE may be due to the conversion of land (Hou et al., 2012). For example, Deng et al. (2006) report that large tracts of unused wetland and unused barren land were converted to cultivated land in northeast China between 1986 and 2000. As previously mentioned, the breadbaskets of Hebei, Shandong and Henan come top with values are ranging from 0.65 to 0.7. These regions have been targeted by policies, such as cropland conservation. Learning from them to improve LUE would be useful for agriculture, including giving local government insight into the rotation of land use.

5. Discussions

China has the highest fertiliser use per hectare globally, but production on average is moderate by global standards. As a consequence, the efficiency of fertiliser is lower than the global average (Huang and Jiang, 2019; Wu et al., 2018). In addition, the excessive use of synthetic fertilisers caused increasing and prevalent water pollutions in China (Yu et al., 2019). Therefore, to achieve sustainability, the application of fertiliser needs to be reduced through the adoption of enhanced management practices in fields (Cui et al., 2018). Pesticides are other critical chemicals in agriculture, and the average pesticide use per

hectare of cropland is between two and seven times that of world average (FAO, 2019). Decreasing its use would not only increase efficiency but also reduce the environmental impact.

We found that the larger-scale farm in Northeast has lower TE, and we guess maybe because of lower multiple cropping since land is the most important in crop production. However, LUE is also lower in Northeast because in our study, we only analyse the efficiency of crop production, but in Northeast, most area is forest, not suitable for cropping. Expansion of cropland to the unfertile land will continue lead to low efficiency. The government should pay more attention to these areas and implement measures that support improving agricultural efficiency.

The limited data on the prices of inputs, including the wages of hired agricultural labour and family labour, resulted in analysis bias for the production function. The spatial weight matrix in this paper was based on geographic contiguity without consideration being given to the economic interaction between counties. This would be an interesting area for further study. Our county-level data for crop production have drawbacks in terms of depth and data quality, which we cannot reduce or account for. More detailed, fine-scale analyses, possibly with primary farm-level data, will deepen the knowledge in farming efficiency. With the development of digital agriculture, a detailed analysis at household or land plot level will substantiate our analysis and provide for specific policies that provide incentives for more sustainable agriculture.

6. Conclusions

To the authors' best knowledge, this is the first empirical analysis using a spatial autoregressive stochastic model (SAR-SFA) to estimate the evolution of land use efficiency (LUE) of agricultural production in China with county level data over more than thirty years. The SAR-SFA model allows estimating the TE and LUE, as well as the determinants behind technical inefficiency. The model allows to examine spatial dependency in crop production by introducing a spatial lag, which substantially improved the estimation performance, as shown by the positively and strong influence of the spatial spill-over effect. This approach hence, allows shedding light on pathways of improving crop production efficiency in China. Identifying and quantifying the effects of the determinants on production performance can help design policies that aim at improving the TE of crop production. Improvements in TE and LUE in agricultural production are crucial if China is

to feed its vast population within the limited arable land and domestic self-sufficiency remains a major goal of the Chinese government.

In order to increase TE, one approach could be better networking or integration between regions, from farm level to province level. Moreover, developing other agricultural sectors, including forestry and livestock, could also contribute to increasing efficiency in crop production. Thus, holistic thinking for agriculture will likely be beneficial for overall development of green sector. Even the elasticities of inputs varied between regions, but overall the declining elasticity of labour is a good phenomenon from another perspective, since a drop in labour or a fall in the demographic dividend is a major problem for farming. Furthermore, increasing machinery would be a substitution for labour.

Appendix IV

The criteria for removal were that the average cropland area between 1980 and 2011 was below 10 thousand ha and less than 10 % of total provincial area. As a result, Inner Mongolia, Xinjiang, Qinghai, Tibet, Hainan, Beijing and Tianjin were excluded from the analysis. There were no data for Taiwan; therefore it was not included in the study. The distribution is shown in the map (A IV-1).



A IV-1. Study area.

Despite the likelihood ratio test, the Akaike information criterion (AIC) (Akaike, 1974) was also used to choose between the fitted stochastic frontier approach and spatial autoregressive stochastic frontier approach models. Furthermore, to check the robustness of the model selection, the Schwarz/Bayesian information criterion (BIC) was also used (Schwarz, 1978). Both criteria are based on a concept that minimises information loss and properly separates noise from structural information (Burnham and Anderson, 2004): in particular, the smaller the AIC and BIC, the less the information loss. The Hausman Test resulted in the rejection of the hypothesis that there is no difference in coefficients, resulting in the fixed-effects model being preferred in the study. Using the likelihood ratio test (LR test), three separate null hypotheses, including translog terms, technical inefficient

items and spatial dependency items, were tested and all rejected (A IV-2). Consequently, the spatial autoregressive stochastic frontier translog function was selected. In addition, there was a strong preference for the spatial autoregressive stochastic frontier model with technical inefficiency over the normal stochastic frontier model and spatial autoregressive stochastic frontier model without technical inefficiency models because the first model yielded a lower value of AIC and BIC than the latter two. The local spatial parameter ρ was also significant at the 1 % level, indicating how the spatial dependence of dependent variable y was affected by the model specification. The following analysis was derived from the fitted spatial autoregressive model (SAR-SFA) model.

A IV-2. Models test and specification.

Test	Hypothesis	LL	AIC	BIC
1.	Specification of effects: $\chi^2(7) = 1040.43$ / $\text{Prob} > \chi^2 = 0.00$			
	H0: difference in coefficients not systematic (RE)	-10372.11	20766.21	20854.24
	H1: difference systematic (FE)	-5654.381	15340.76	31473.38
2.	Selection of production function LR $\chi^2(15) = 450.68$ / $\text{Prob} > \chi^2 = 0.00$			
	H0: Cobb-Douglas production function	-5654.381	15340.76	31473.38
	H1: translog production function	-5429.039	14920.08	31172.73
3.	Specification of technical inefficiency model LR $\chi^2(11) = 2840.27$ / $\text{Prob} > \chi^2 = 0.00$			
	H0: no technical inefficiency effect	-5429.039	14920.08	31172.73
	H1: final specification as Model 1	-4008.902	12101.8	28442.48
4.	Specification of SAR LR $\chi^2(1) = 4533.84$ / $\text{Prob} > \chi^2 = 0.00$			
	H0: $\rho=0$ no spatial dependency	-4008.902	12101.8	28442.48
	H1: final specification as Model 2	-1741.983	7569.966	23918.65

Note: AIC – Akaike information criterion, BIC – Bayesian information criterion, LL – log likelihood value

Chapter V. Synthesis

1. Summary

The overarching objective of this thesis was to develop a quantitative understanding of spatial dynamic patterns, determinants, and causes of cropland, production and productivity changes across China from 1980 to 2011. To achieve this goal, we used county-level panel data across all China and employed various spatial data analysis methods, including spatial exploratory statistics, spatial panel models, and spatial stochastic frontier approach. Three research questions associated with the overall objective are answered in three chapters (Chapter II, III, and IV), respectively.

Research Question 1 (Chapter II): What were the spatial patterns of changes in cropland area and major crops harvested area from 1980 to 2011?

In Chapter II, I analysed the changes of cropland and harvested area of five major crops, rice, wheat, maize, soybeans and potatoes. Specifically, global Moran's I and General Entropy Index (GEI) were used to measure the trend of spatial concentration of cropland and five major crops, calculated from county-level statistical data. Additionally, hotspot and cold spot maps of each crop were produced based on local indicators of spatial association (LISA) to present intuitively the changes in spatial patterns of cropland and harvested area of the major crops.

Results show that cropland and the major crops harvested area in China had been increasingly concentrated from 1980-2011. The spatial clustering, measured by Moran's I, of cropland and most of crops exhibited modest growth over the study period. The spatial inequality, measured by GEI, became higher for major crops especially soybean and maize—these two crops experienced the most dynamic changes since 1990. Both crops became more concentrated, despite diverging trends in their harvested areas: a substantial increase for maize vs a decrease for soybeans. Furthermore, the hotspot of cropland and major crops harvested area were found to be concentrating, especially since 1990, in Northeast and North China—the major historic breadbaskets of China with favourable geographical and environmental suitability.

The increasing concentration, which likely continued after year 2011, may have positive effects on crop productivity through spill-over effects of technology, processing facilities, and knowledge. The increasing specification leads to higher efficiency and productivity. Thus, it can enhance the food security of China. And it may benefit the recovery of nature in areas where crop production has contracted in terms of area used and of cultivation

intensity. However, a higher concentration of staple crops production may also lead to higher vulnerability to climate change, natural hazards, and disease outbreaks. Additionally, the lower crop diversity may also have negative environmental effects, directly and indirectly. For example, soybeans have been converted to wheat, maize and rice in many regions. The resulting nitrogen deficiency in the soil leads to excessive usage of synthetic fertilizers, which cause nitrogen pollution and lower agricultural income (Sun et al., 2018). Conserving the crop diversity not only benefits self-sufficiency but is also good for the sustainability of the environment.

This research revealed the complex dynamics of the spatial concentration in cropland and major crops in China, and we envision these results to foster the implementation of mitigation measures that reduce agricultural production risks and enhance the resilience of the agricultural production system.

Research Question 2 (Chapter III): What were the determinants of changes in harvested area and yields of major crops?

Following the study on the concentration trend of cropland and harvested area of major crops, in Chapter III, I used a spatial autoregressive model to analyse the determinants of harvested area and yield changes of the major crops (rice, wheat, maize and soybean) based on county-level panel data. Statistics show that the average harvested area of maize increased, while that of rice and wheat decreased. The harvested area of soybeans decreased over time, particularly after trade liberalization following China's WTO accession. The yields of rice, wheat, and maize increased substantially, mainly due to the higher input intensity, such as more fertilizers and machinery usage. The yield of soybean, however, decreased by 33% from 1980 to 2011.

The spatial panel model was used to better understand the determinants affecting the harvested areas and yields of major crops over time and space. We applied a spatially explicit panel regression analysis with both spatial heterogeneity and spatial dependency. Results can be summarized as follows:

Firstly, the results confirmed the spatial clustering pattern for all crops, as the spatial lag effect was positive. Secondly, the effects of determinants were heterogeneous among the major crops. Taking road length in a county as an example, longer road length was associated with less harvested area of rice and soybean, but harvested areas of wheat and maize tended to increase. Thirdly, increasing food demand (proxied by population) and increasing inputs (labour and machinery) were associated with increased harvested areas.

Fourthly, crop yields are, not surprisingly, closely correlated with agricultural input, including machinery and fertilizer. Lastly but not least, WTO accession in 2001 was associated with an increase in wheat and maize yields, while it had a negative effect on rice and soybean yields.

As a result of the increasing grain yields, China is almost self-sufficient in rice, wheat, and maize production despite its increasing domestic demand. However, the liberalization of trade has driven stagnation in domestic soybean cultivation as majority of soybeans consumed are imported. On the other hand, trade also promotes the trend of spatial concentration over the whole world as well as within China. Yield increases benefit mostly from more utility of inputs, especially the modern ones, including machinery and fertilizers.

Overall, our analysis demonstrates the complex interactions among intertwined determinants affecting the area and yield changes in China. In light of the many impacts of changes in crop production on food security and the environment, it is important to reveal the patterns and determinants of such changes across large areas. Analysis to better understand the determinants driving such changes will also benefit from longer time series and methodological improvements, such as in spatial econometrics that allow for a deeper analysis of space-time data. The sustainable development of Chinese agriculture can benefit greatly from evidence-based decision making with data-driven insights.

Research Question 3 (Chapter IV): What were the determinants for the observed changes in land use efficiency and how do these vary across time and space?

The agricultural production increase in China over the past years is due mainly to increasing input intensity. As land is the most indispensable and also scarce natural resource for China's agricultural production, improving land use efficiency in China is critical for sustainable agriculture and food security. We therefore focus on the spatial and temporal change of land use efficiency and its determinants in Chapter IV. By introducing spatial spill-over into a production function, we used the spatial autoregressive stochastic model (SAR-SFA) to estimate the technological efficiency (TE) of crop production and land use efficiency (LUE) in China at county level from 1980 to 2011.

TE showed an increasing trend, but varied spatially. Overall TE increased by 20% but varied between regions, with a lower percentage in the northeast and northwest, and a higher percentage in North China and South China. Even the elasticities of inputs varied between regions, but overall the declining elasticity of labour is a good phenomenon from another perspective, since a drop in labour or a fall in the demographic dividend is a major

problem for farming. Furthermore, increasing machinery seems to be a substitution for labour. What's more, the importance of land is still the highest among the five inputs—land, labour, machinery, fertilizer and pesticides—but showed a decreasing trend. Analysing the determinants of TE, we found urbanization resulted in a lower TE of crop production, while the regions with a greater distance from the nearest provincial capital had a higher TE. The LUE and TE of crop production were positively correlated.

Our findings reveal that land use efficiency has not increased at the same rate as yield has increased, and production growth in China is mostly from increasing inputs. Efficiency also showed a positive spill-over effect. Thus, it justifies the need to model with spatial lag. With the decreasing importance of land, we call for the introduction of more scientific and highly technical cropping system for crop production in China.

To the authors' best knowledge, this is the first empirical analysis using this model to estimate the evolution of land use efficiency (LUE) of agricultural production in China with county level data over more than thirty years. The SAR-SFA model allowed the estimation of TE and LUE, as well as of the determinants behind technical inefficiency. The model allowed the examination of spatial dependency in crop production by introducing a spatial lag, which substantially improved the estimation performance, as shown by the strong positive influence of the spatial spill-over effect. Hence, this approach sheds light on the pathways of improving crop production efficiency in China.

Identifying and quantifying the effects of the determinants on production performance can help design policies that aim to improve the TE of crop production. Improvements in TE and LUE in agricultural production are crucial if China is to feed its vast population on its limited arable land and domestic self-sufficiency remains a principal goal of the Chinese government. In order to increase TE, one approach could be better networking or integration between regions, from farm level to province level. Moreover, developing other agricultural sectors, including forestry and livestock, could also contribute to increasing efficiency in crop production. Thus, holistic thinking for agriculture will likely be beneficial for the overall development of the Green sector.

To sum it up, the three individual research questions are addressed in each of chapter II, III and IV. Together, the results help us to achieve the overall objective: to better understand the patterns and determinants of agricultural land use and production over the study period. In short, we show that over three decades, land use in China concentrated increasingly on a few major crops, driven in part by the policy of self-sufficiency in staple crops, including

rice, wheat and maize. Additionally, land use gradually concentrated in the areas with suitable ecological conditions and in areas that are located close to the main centres of consumption. Moreover, trade plays an increasingly important role in crop patterns. Crop production increased substantially with increasing inputs and technical efficiency. However, the partial technical efficiency of land, which is defined as land use efficiency in this thesis, has a larger gap than technical efficiency. It is vital that increasing the land use efficiency also increases the efficiency of crop production. Moreover, machinery plays an increasingly important role in crop production. From this study, the results contribute to a better understanding of the patterns and the changes thereof, of the major crops harvested area, cropland and crop production, and help inform decision makers of spatial difference and dependencies.

2. Significance

As the most populous country in the world with a rapidly developing economy, China's agricultural production and food security is not only a top concern of the Chinese government, but also a global matter. This is best illustrated by the famous questions raised by Lester Brown, "Who will feed China?" and "Can the world feed China?" (Brown, 2014). To date, these questions are still very much valid despite the substantial increase of agricultural production in China after rural reform kicked off in the late 1970s. Land is the most indispensable natural resource for agriculture, and in China it is scarce. China feeds 20% of the world's population on 7% of the world's farmland. Land is the core issue of agricultural production and food security. This entails not only cropland area, but also the spatial patterns of crops, land use efficiency and productivity. This thesis is aimed to tackle this core issue with fine-scale and long-term panel data, a very rare dataset, and various state-of-the-art spatial statistical models. The findings in this thesis span important aspects of land system changes, including area extent and input intensity, at high temporal resolution. The quantitative analyses, combining spatial and temporal dimensions, provide a systematic and holistic understanding of the agricultural land use and food production in China during a period of historically unprecedented economic growth.

Better understanding of the spatiotemporal developments of land use change and crop production could support policy makers as they guide and plan land use toward sustainable and profitable pathways, not only in China but in other countries with similar situations. The spatial heterogeneity and concentration patterns of crops promote localized policies

and measurements. For example, the major breadbasket regions need favourable policy support for crop production; at the same time, policy priority should be focused on multi-functional agricultural land and ecosystem services in the marginal production regions. The overall increasing crop concentration may lead to higher efficiency and productivity, but policy makers need to be aware of the associated risks and vulnerability to climate change, natural hazards, and disease outbreaks. The changes in harvested crop areas and yields are driven by the complex interactions among intertwined determinants including climate and socioeconomic factors. In addition, the interactions among crops and interconnected food systems via trade further add complexity to food production. Holistic and adaptive policies need to be put in place to guide sustainable agricultural production in China.

From a scientific and methodological perspective, the multidisciplinary approach of combining geographical methods and economic models reflect the state of the art of land system research. The various methods used in this thesis such as spatial explorative statistics, spatial panel models, and spatial autoregressive stochastic frontier models are promising tools in analysing complex agricultural land use systems. The spatially explicit method is gaining increasing attention in the field of agricultural economics. Economic theory and quantitative methods can help geographers explore the determinants and causes behind these spatial patterns. This thesis demonstrated the advantages of such approaches and methods by producing results and insights, which would not be possible with a single-disciplinary approach. The innovative application of GEI in the spatial concentration of croplands and the spatial autoregressive stochastic frontier analysis also contributed to the development of the methodology. I believe such approaches and methods can stimulate further research along this line.

3. Critical reflections and Outlook

3.1 Critical reflections

This thesis has explored the data utility and methodological capacity for agricultural land system and land dynamics in China. Our national-level analysis at the relatively coarse resolution of counties spanning a period of 32 years clearly reveals some pertinent trends in crop production in China. Even the data, which is a rare and veritable ours of information, it is still limited. For example, data quality is still in question especially in the early 1980s. The statistical data in China at the county level is not very consistent, and there are many missing data points, which we have had to interpolate with trends and other data sources.

The collection of data from other sources brought with it degraded quality and no accuracy estimate. Moreover, these data may be biased because of the structure of reporting and the tendency of local authorities to report better-than-actual numbers. More detailed, fine-scale analyses, possibly with primary farm-level data will enrich the dataset. With the development of digital agriculture, a detailed analysis at household or land-plot level will substantiate our analysis and provide for specific policies that provide incentives for more sustainable agriculture. In addition, the data is a little out of date, and we do not have statistics for most recent years, i.e., after 2011, since the data collection and management became more difficult and complex.

Secondly, spatial panel models have rarely been used in land use system science. While I planned to compare the results from different software programs to check the accuracy of results, it did not work out. The algorithm is not time-efficient, one model regression needs much time, and when the size of observations is large, the spatial weight matrix becomes accordingly large, and the calculation requires one day for one model. Another limitation is the hypothesis for the spatial weight matrix. Even though we compared different geographical weight matrices in this study, these weight matrices could only represent a limited connection, ignoring the interaction between regions that may be distant but have close economic ties. This thesis had tried to combine the geographic and economic sectors, but there are still more details and issues to solve.

3.2 Outlook

Some important topics, which were initially beyond the scope of this study, also emerged during the course of this thesis.

In this thesis, I analysed the changes of cropland and crops, but agriculture includes not only crops production or cropland dynamics, but also other agricultural production, such as livestock, fishing and forestry. Besides land, water is another critically scarce natural resource in China, and it would be interesting to investigate water resources and their interactions with agricultural land and crop structures. Including these production systems and natural resources may provide a comprehensive picture of Chinese agricultural production.

We looked at patterns, determinants and drivers of land use change, but it would also be important to analyse the impact of such observed changes in land use on the environment and economy. Agriculture, as a major means by which humans alter environmental and natural systems, has modified entire landscapes and altered plant and animal communities,

and ultimately ecosystem services. In turn, deteriorating the environment and ecosystem services constrain the capability of food production and hurt human welfare (Ojima et al., 1994; Turner et al., 1990). It is crucial to consider the tradeoffs and synergies in agriculture for sustainability (Verburg et al., 2015). Agriculture affects the soil quality, water resources, biodiversity, and global greenhouse gas emissions. It is critical that future earth programmes study how to achieve a balance and how to make the earth systems less vulnerable and more stable, and ultimately sustainable for human living. Agriculture is not like most industry, specification or monoculture may benefit productivity, but that will decrease local biodiversity and may even damage the environment, leading to the problem that it missed the vital link with agricultural sustainability and farm system resilience (Coomes et al., 2019). Food demand and consumption are always the main drivers for production, and food production is a major driver of land use (Aleksandrowicz et al., 2016). With changes in diet, demand has changed accordingly, and therefore, shifts in dietary patterns can potentially support sustainability for both environment and health.

Specialization is the future of agriculture, but how to maintain both high productivity and sustainability is still the big question. Precision farming and technological advancements along the supply chain can help address these challenges and meet rising global food demand, driving the next agricultural revolution (Walter et al., 2017). The transition of economic development from industry-based to information-based will lead to a transformation in agriculture. In the digital era, of all the inputs that can maximize yields, including traditional inputs such as land and labour, and modern ones such as science, technology, and machinery, the most critical is information. Remote sensing techniques from in-field sensors to drones (Floreano and Wood, 2015) to satellite imagery (McKinion et al., 2004), are allowing farmers or decision makers to view more information from multiple perspectives (Planet Labs, 2018). The new technologies also require new adjustment. Observed climate change is already affecting food security through increasing temperature, changing precipitation patterns, and a greater frequency of extreme events. Adaptation for these observed and potential climate changes will necessitate more information and technology.

The importance of trade for crops and agricultural production was shown in the analysis of determinants. Trade connects people economically. Further tracking the influence of trade on agriculture, locally and globally, would allow better resource allocation. In one aspect, since hunger mostly occurs in developing countries, and food waste occurs mostly in developed countries, transportation and trade are needed. International trade in agricultural

products accelerated rapidly after 2001, but most recently the growth has been sluggish. To further liberalize agricultural trade, change the rules on food safety, animal and plant health, and harmonize food product standards, three large regional trade agreements (RTAs) have recently been concluded or are under negotiation: the Trans-Pacific Partnership (TPP, in 2018), the Regional Comprehensive Economic Partnership (RCEP, not in force), and the Transatlantic Trade and Investment Partnership (TTIP, under negotiation) (FAO, 2017). In another aspect, trade of agricultural commodities for domestic and foreign markets increasingly changes global land use and carbon emissions, for example deforestation in tropical regions (Henders et al., 2015), and biodiversity loss in developing countries (Lenzen et al., 2012). To solve these global issues, including trade in the earth systems is needed.

Continuing the analysis of crop production and land use efficiency will help us understand agriculture more. Increasingly intensive land use systems seem to be evolving in new, more land-efficient, directions that may even reverse many of the environmental impacts of prior land use (Stephens et al., 2019). Research on how to increase and allocate technical efficiency to improve productivity is vital when land is fixed and limited. In addition, population, per capita demand, and total food production are three factors affecting the potential to satisfy global food needs (Tamburino et al., 2020). Rapid population growth is one of the key drivers of vulnerability to impacts, and therefore not only production-oriented studies but also a focus on diets and population (Willett et al., 2019) is necessary to provide adequate information for policy makers. The size of the human population is not the only variable stressing the Earth, but it is the most powerful. We want to build up a healthy world, where there is no land degradation, no species lost and no food waste. These targets need not one field of researchers, but rather a multitude of interdisciplinary researchers working together to think wider and deeper towards a sustainable earth.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Dokortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Fang Yin

24.02. 2020

Ich erkläre, dass die von mir in der Universitätsbibliothek abgegebene schriftliche und elektronische Version der Dissertationsschrift mit der angenommenen Dissertation übereinstimmt und nur kleine Rechtschreibkorrekturen enthält.

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